

HERIOT-WATT UNIVERSITY

DOCTORAL THESIS

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# Essays on Macro-Finance

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## **Joint Work Declaration**

Chapter 2 is joint work with Prof. Joseph Byrne (my first supervisor), with my contribution being 85% of the work.

# Abstract

This thesis on topics in macro-finance, considers the relationship between the macroeconomy and also financial markets. We examine the key predictors, including macro determinants and technical indicators, of returns to the US stock market. Moreover, we investigate the links between financial markets internationally. We also study the importance of financial factors for monetary policy.

In more detail, Chapter 2 constructs a flexible Bayesian framework to predict the equity premium, allowing for abrupt or gradual or even no changes in forecasting models and in coefficients. This approach has out-of-sample predictive power statistically and economically. Moreover, this model dominates its nested combination methods, including equal-weighted models, Bayesian and dynamic model averaging. By decomposing the prediction variance, we find that our approach precisely identifies the locally appropriate time variation in coefficients and the forecasting model over time, leading to mitigation of estimation risk.

We then go on in Chapter 3 to model and predict financial integration, given the rapidly evolving nature of financial globalization. Importantly, this chapter allows national exposure to the global financial factors and the process driving volatility to vary over time. The obtained results show that financial integration is highly predictable, which has implications for international diversification, risk management and policy making. The CBOE volatility index (VIX) is identified as a strong predictor of financial integration, reflecting the vulnerability of financial markets to uncertainty.

Our third main chapter, Chapter 4 studies how the impact of monetary policy shocks interact with the financial environment, in particular with financial uncertainty. The work identifies that monetary shocks have stronger, but less

persistent, effects during periods of elevated financial uncertainty compared to more tranquil periods. These differences in effects among the uncertainty-dependent states suggest that nonlinearities in the credit channel are stronger in the short run, whereas in the long run nonlinearities in the interest rate channel dominate.

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# Chapter 1

## Introduction

### 1.1 Motivation

Financial markets play a critical role in economic growth and stability. The former British Prime Minister William Gladstone expressed the importance of finance for the economy in 1858 as follows: *“Finance is, as it were, the stomach of the country, from which all the other organs take their tone.”*

Macro-finance studies the link between asset prices and economic fluctuations. More specifically, the stock market provides signals to business confidence and further to consumer spending. As a consequence, investors, economists and policy makers pay close attention to stock market prices for hints about future economic performance. Figure 1.1 plots the NYSE price-dividend ratio and the detrended consumption. We can tell that cyclical movements in stock prices and consumption are strongly correlated, especially after 1999. Stock returns also help to predict macroeconomic variables such as GDP growth, unemployment rate and inflation.<sup>1</sup>

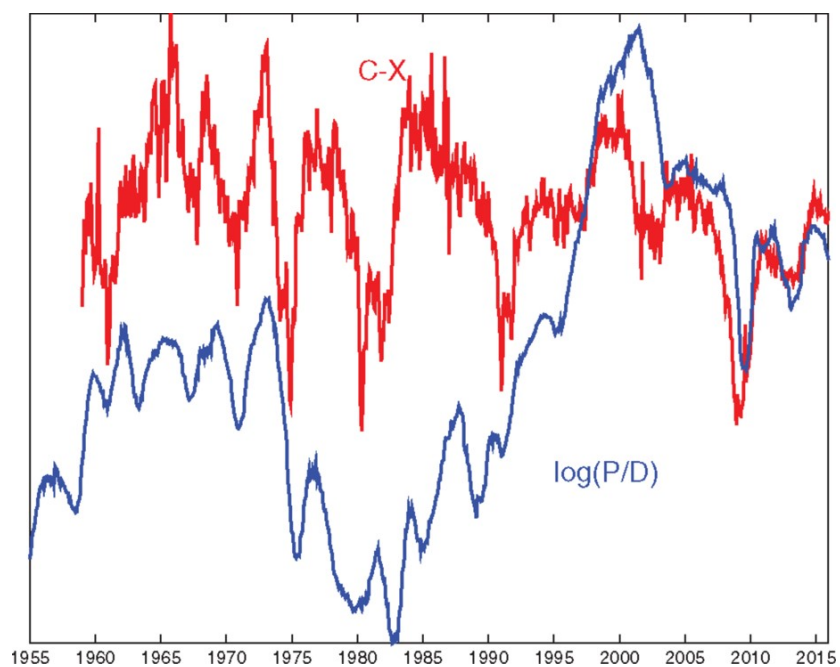
Academic researchers have sought to model empirically the link between financial markets and the macroeconomy. The financial economics literature

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<sup>1</sup>See reviews in Cochrane (2009, 2011, 2017).



FIGURE 1.1: Stock Price-dividend Ratio and Detrended consumption. Source: Cochrane (2017)



*Notes:* This figure plots the NYSE price-dividend ratio and the detrended consumption.  $\log(P/D)$  is the log ratio of price to dividends of the value-weighted NYSE CRSP index.  $C - X$  represents the difference between log total real per capita consumption  $C$  and its moving average  $X_t = \phi X_{t-1} + (1 - \phi)C_t$ , with  $\phi = 0.9$ .

suggests that excess equity returns vary over time and correlate with the business-cycle. We can forecast stock returns as follows:

$$R_{t+1}^e = a + by_t + \epsilon_{t+1} \quad (1.1)$$

where  $R_{t+1}^e$  is the equity premium in the next period (i.e. stock returns minus treasury bill rate) and the forecasting variable  $y_t$  includes dividend yield, earnings-yield ratios or interest rate spread etc. Welch and Goyal (2008) systematically investigate the existing predictors for excess returns in the literature and claim that none of these predictors have in-sample or out-of-sample predictive power using ordinary least squares (OLS) estimation of key parameters  $a$  and  $b$ . Chapter 2 therefore starts from one of the most prominent areas of study in financial economics: time-series stock return predictability. This chapter focuses on the problems of model uncertainty and parameter instability, that simple OLS ignores. It does so by capturing the locally proper degree of time-variation in coefficients and in forecasting models over time.

In recent decades, increasing globalization has driven investors to pursue higher rates of asset return and the chance to diversify risk internationally. At the same time, many economies have encouraged financial flows by easing restrictions and regulations on foreign direct investment and removing controls on portfolio capital inflows and outflows. The fast growing financial markets and the surge of cross-country financial flows have sparked great interest in this area within international finance. The potential benefits of financial integration include international risk sharing for consumption smoothing, more efficient capital allocation and greater investment opportunities. The cost of financial integration includes increased competition to access international funds, especially for small countries, and a vulnerability to global financial

market. This relates to spillover effects and contagion risk.<sup>2</sup> The previous literature widely uses cross-country correlation of asset returns to measure price-based financial integration.<sup>3</sup> However, this measure has been heavily criticized in the literature. For instance, Pukthuanthong and Roll (2009) argue that even perfectly integrated stock markets can be weakly correlated. Moreover, integration drawn from cross-country correlations may be biased as a result of the conditional heteroskedasticity of stock returns, as suggested by Forbes and Rigobon (2002) and Volosovych (2011). Chapter 3 consequently adopts an intuitive measure of integration: the proportion of an economy's returns which can be explained by global factors, following Pukthuanthong and Roll (2009) and Eiling and Gerard (2014). Additionally, a dynamic model is employed to capture structural changes in the economy by allowing for time-varying loadings and stochastic volatility over time and the predictability exercise is conducted to provide insights for investors and policy makers.

As we know, from 2007, the global financial market went through a period of substantial turbulence which started with a crisis in the subprime mortgage market in the United States, and this triggered significant disruptions globally in different sectors of the financial markets. Meanwhile, a number of financial markets such as equities, foreign exchange, as well as commodities have underwent heightened volatility and uncertainty. In particular, economists concerned about tightening money markets and reduced liquidity, with increase degree of asymmetric information in credit markets and severe strain in market liquidity. As the most important means to maintain inflation and stimulate the economy, monetary policy responded to this great recession by cutting interest rate and employing unconventional monetary policy tools. These policies aimed to ease financial condition and promote business during times of

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<sup>2</sup>See, Agénor (2001), Kose et al. (2009), and Billio et al. (2017) for reviews.

<sup>3</sup>See among others, Goetzmann et al. (2005) and Quinn and Voth (2008).

uncertainty. Nevertheless, González-Páramo (2008) claims that the intensification of the financial market turmoil poses great challenges for the formulation of monetary policy. Moreover, increased counterparty credit risk has partially debilitated the monetary policy transmission mechanism. It is therefore extremely crucial to understand the empirical effectiveness of monetary policy during periods of high financial uncertainty. This is the starting point of Chapter 4 and it has important implications on handling the stress from the financial market using monetary policy.

## **1.2 Contributions**

This thesis makes various contributions to the asset pricing, international finance and monetary policy literature. Chapter 2 contributes to financial economics by constructing the dynamic mixture model averaging (DMMA) method to allow for possible degrees of time variation in coefficients and in forecasting models in the stock return predictive regressions. This framework nests gradual to abrupt and even no change in coefficients and in forecasting models. Especially, the DMMA method fits in the environment that investors may rapidly adjust their beliefs on the relative importance of equity predictors in times of stress and less quickly when turbulence abates. By contrast, although the dynamic model averaging (DMA) developed by Raftery et al. (2010) and Koop and Korobilis (2012) allows for time-varying coefficients and forecasting models, the degree of variation is fixed over time. The contribution of Chapter 2 goes beyond merely constructing this new approach to predict excess stock returns and comparing it with alternative models statistically and economically. A key innovation of our approach is that it is a sufficiently flexible framework to allow us to decompose prediction variance and analyze what leads to forecasting improvements. We are able, therefore, to investigate the

relative importance of five elements contributing to forecast failure: observational variance; coefficient estimation risk; predictor selection; and the speed of updating of time-varying coefficients and forecasting models. Furthermore, we examine whether the predictability of DMMA is linked to the business cycle. The importance of individual predictors and the optimal degrees of time variation in coefficients and in forecasting models are also explored.

The next chapter contributes to the literature by considering international financial linkages. The main contribution of the analysis in Chapter 3 is the construction of a time-varying financial integration measure for 18 advanced economies. A natural approach to measure integration is via a factor model, in which the expected stock return of each country is driven by global factors extracted from the stock markets. Factor models are ideal since they can summarise co-movement of economic and financial quantities (see *inter alia* Del Negro and Otrok (2008) and Byrne et al. (2013)). Financial integration is then measured as the proportion of a country's stock return explained by the global factors. Instead of the common assumption of constant loading and volatility in the factor model, this chapter allows for time-varying loadings and stochastic volatility, to capture short run transitory and long run structure changes in the measure of financial integration.

The second contribution in Chapter 3 is the understanding of the mechanism behind the cross-country differences and trends in financial integration. The method this thesis adopted is advantageous in decomposing financial integration into systematic risk of global factors, local factor and estimation error over time and examine which components are the drivers of financial integration. Finally, Chapter 3 provides evidence about the predictability of financial integration based upon economic fundamentals, including the CBOE volatility index (VIX) index. This is the first work that attempts to predict financial

integration and therefore has potential implication in terms of portfolio diversification, risk management and policy making. (see, among others, Blanchard et al. (2010), Donadelli and Paradiso (2014), and Castiglionesi et al. (2017)).

Chapter 4 contributes to the macro-finance literature by studying the ways in which the impact of monetary policy shocks interact with financial uncertainty. The literature has argued that unlike economic uncertainty, financial uncertainty is the key origin and propagating mechanism for business cycle fluctuations, see for example, Ng and Wright (2013) and Ludvigson et al. (2015). However, little work has been done to identify how financial uncertainty impact other important structural shocks such as monetary shocks. Therefore, this chapter investigates the effectiveness of monetary policy during high vs low financial uncertainty states. Contrasting with the previous literature that takes the economic uncertainty in Jurado et al. (2015) and the VIX index in Bloom (2009) as uncertainty indicators, the broad based measure of financial uncertainty of Ludvigson et al. (2015) is employed, which extracts the variance of the unforecastable components from a large financial dataset. This uncertainty measure is more advantages because it truly focuses on the unexpected movements in the financial market and investigates uncertainty not only from the equity market.

The second contribution of Chapter 4 is the investigation of the theoretical linkage between financial uncertainty and the effectiveness of monetary policy shocks. This thesis identifies nonlinearities in both the interest rate and the credit transmission channel and is the first one that systematically assesses all the possible explanations proposed in the literature.

## 1.3 Research Questions

This thesis proposes and answers a number of research questions associated with macro-finance. For instance, to successfully predict excess stock, in Chapter 2, the following questions are considered: Is it important to account for different degrees (faster and/or slower) of time variation in coefficients or constant parameters models are preferred? Is it possible to uncover the existence of optimal forecasting models for stock return predictability? How important in absolute and relative terms are the problems of parameter instability and model uncertainty for stock return predictability? Does the approach constructed in this thesis show a better predictive power compared to alternative models? If so, what drives this predictability?

Financial integration among the advanced economies is investigated in Chapter 3 and the following research questions are answered: how important are time-varying coefficients and stochastic volatility when modelling financial integration in the international Capital Asset Pricing Model (CAPM) framework? Has global financial market integration increased over time due to the surge of capital flows or other economic and regulatory changes? What drives and predicts the dynamics of financial integration? Is the increasing financial integration due to increasing global risk or decreasing country-specific effect? Moreover, is the CBOE volatility index (VIX) informative about the movements of financial integration?

The impact of financial uncertainty on the effectiveness of monetary policy is explored in Chapter 4, where the specific research questions below are considered: Is the impact of monetary policy shocks on the economy and financial market different during high financial uncertainty periods compared to low financial uncertainty periods? If so, what are the driving forces behind these differences? Finally, are the results consistent with the existing explanations

for state dependent responses of monetary policy shocks, as discussed in the literature?

## 1.4 Methodology

In this section, the econometrics methods applied in this thesis are briefly summarised. In Chapter 2, the dynamic mixture model averaging model (DMMA) is proposed to predict stock return. This method is based on the dynamic model averaging (DMA) method suggested by Raftery et al. (2010) and Koop and Korobilis (2012). However, DMA assumes that coefficients and forecasting models change in the same fashion over time. This fixed dynamics for evolution would be inappropriate as some model specifications shall only be suitable for some periods as investors may shift the importance of predictors when economic and financial conditions vary. This chapter therefore constructs DMMA, which allows for possible degrees of time-variation, nesting gradual to sudden, or even no changes in coefficients and in forecasting models. DMMA is advantageous in detecting locally appropriate coefficients and forecasting models. Additionally, the econometrics framework of DMMA allows us to decompose the prediction variance and investigate what leads to forecasting improvements compared to alternative models. Especially, the following five parts comprise prediction variance: (i) uncertainty due to random fluctuations in data (*observational variance*), (ii) uncertainty respecting coefficient estimation error (*estimation risk*), (iii) model uncertainty caused by predictor selection, (iv) model uncertainty regarding the degree of time variation in coefficients, (v) model uncertainty due to the magnitude of time variation in forecasting models.

Chapter 3 first employs the out-of-sample principal component analysis



(PCA) to extract global factors from the 18 stock markets this thesis considers. The number of principal components is determined by the Bai and Ng (2002) information criteria test. Then a Bayesian model with time-varying coefficients and stochastic volatility is used to capture the dynamics between the global factors and stock return for each economy. The time-varying financial integration is measured as the total variance explained by the global factors. The advantage of this flexible model to measure integration is that it does not depend on rolling window or recursive estimates, but explicitly models time-variation in the coefficients and volatility from the data. Besides, it captures the short- and long-run economic and regulatory changes that may affect the measurement of financial integration. Perron and Yabu (2009a) trend test and Perron and Yabu (2009b) break test are adopted to study the characteristics of financial integration. To predict financial integration, Chapter 3 applies the dynamic model averaging acknowledged by Raftery et al. (2010) and Koop and Korobilis (2012) to take the problem of parameter instability and model uncertainty into account. The importance of different predictors can be further investigated over time.

In Chapter 4, a smooth transition vector autoregression (STVAR) is adopted to study the effectiveness of monetary policy during high vs low financial uncertainty states. The advantage of STVAR compared with linear VARs for each financial state is that it can effectively extract information from the data, thus, the estimation and inference for each state is more stable and precise. In comparison with other nonlinear VARs such as the Markov-Switching VAR (VAR), STVAR focuses on the underlying variable that drives the asymmetry responses, whereas MSVAR ignores this mechanism and the transition between different regimes can be sudden. Importantly, this thesis computes the generalized impulse response functions (GIRFs) following Pesaran and Shin

(1998), to take both the endogenous response of financial uncertainty to the expansionary monetary shock and its feedback on the system into account. The contribution of monetary shocks on the dynamics of variables during high vs low financial uncertainty periods is obtained using the generalized forecast error variance decomposition (GFEVD), following Lanne and Nyberg (2016).

## 1.5 Results

The empirical results in Chapter 2 suggest that the novel dynamic mixture model averaging (DMMA) model generates more accurate forecasts compared with the historical mean (HM) benchmark across different sample periods. These statistical gains also lead to economic profits for a mean-variance investor. Importantly, with regard to point accuracy, DMMA dominates its nested model combination methods including Bayesian model averaging (BMA), dynamic model averaging (DMA) and equal-weighted models. By decomposing the variance of prediction uncertainty, our flexible DMMA approach more precisely identifies the time variation in coefficients and the combination method we should apply, leading to mitigation of estimation risk and forecasting improvements. In the end, the business cycle analysis is conducted. The obtained result shows that DMMA has better out-of-sample performances during recessions compared with expansions.

The analysis in Chapter 3 finds that the financial integration for the 18 advanced economies considered in the thesis generally displays an upward trend in recent decades. However, none of the economies consistently achieve full financial integration. This greater integration is mainly driven by the greater importance of global factors, not diminishing local effects. Furthermore, financial integration is highly predictable. In addition to a measure of international trade, the CBOE volatility index (VIX) is identified as a strong predictor of

financial integration. This reflects the vulnerability of financial system to uncertainty.

In Chapter 4, empirical evidence is presented that monetary shocks have stronger, but less persistent, effects during periods of elevated financial uncertainty compared to tranquil times. These differences in effects among the uncertainty-dependent states stem from nonlinearities in the credit and interest rate channel. Specifically, in the short run, the credit channel dominates in the way that external finance premium (EFP) are more sensitive to the interest rate drop during financial fluctuations than normal periods, promoting stronger responses of financial and real economy variables. In the long run, however, partial irreversibility of investment, precautionary savings and uncertainty-dependent price-setting mechanism effects prevail, making monetary policy less effective when financial uncertainty is high.

## Chapter 2

# Stock Return Prediction with Fully Flexible Models and Coefficients

### 2.1 Introduction

Stock return predictability is a core area of financial economics and there is extensive evidence that excess returns can be predicted.<sup>1</sup> In approximately equal share however the literature is skeptical about the out-of sample performance of standard models.<sup>2</sup> For instance, Welch and Goyal (2008) comprehensively investigate the predictive power of commonly used asset pricing indicators and find that they forecast poorly both in-sample and out-of-sample using simple linear models. They also point out that forecast performance is unstable and only improves for some predictors in specific periods of stress, suggesting the presence of parameter instability and model uncertainty.

Indeed, the flexibility of the forecasting model and the choice of the predictors both have explicit influence on stock return predictability. To be specific, two broad challenges for stock return predictability have been pointed out by

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<sup>1</sup>See, for example, Fama and Schwert (1977), Fama and French (1988), Kothari and Shanken (1997), Baker and Wurgler (2000), Lettau and Ludvigson (2001), and Andrew and Geert (2007) among many others.

<sup>2</sup>For more general overviews see, for example, the discussion of Goyal and Welch (2003), Cooper and Gulen (2006), Andrew and Geert (2007), Campbell and Thompson (2008), Welch and Goyal (2008), Joscha and Schüssler (2014), and Turner (2015).

the literature. The first challenge is parameter instability such as time-variation in coefficients (see Stambaugh (1999), Andrew and Geert (2007), Wachter and Warusawitharana (2009), Dangl and Halling (2012), and Johannes et al. (2014)). For instance, Andrew and Geert (2007), among others, clearly find evidence of time-evolving parameters by separating the entire sample into different subsamples. The second challenge is model uncertainty (see Avramov (2002), Rapach et al. (2010), Dangl and Halling (2012), and Billio et al. (2013)). As a large array of excess stock return predictors have been suggested by the literature, how to extract useful information from them should be considered. Rapach et al. (2010) study the benefits of combining individual models using equal model weights. Dangl and Halling (2012) investigate stock return predictability by combining dynamic linear models with Bayesian model averaging (BMA) and find out-of-sample gains.

Although there is evidence that taking both parameter and model uncertainty into account improve forecast accuracy, the exact nature of time variation in parameters and how to accommodate model uncertainty remain unresolved. To successfully predict excess stock returns, this chapter starts from the dynamic model averaging (DMA) method developed by Raftery et al. (2010) and Koop and Korobilis (2012). DMA assumes that coefficients and forecasting models are time-varying, however, they typically vary in the same fashion: that the degrees of time-variation in coefficients and in forecasting models are fixed over time. Harrison and West (1999) suggest that the fixed dynamics for evolution is unappealing and some model specifications shall only be appropriate for some periods. For example, investors may rapidly update the relative importance of equity predictors in times of market stress and less rapidly when turbulence abates. We, therefore, develop dynamic mixture model averaging (DMMA), which extends DMA and allows for possible degrees of

time variation, nesting gradual to abrupt changes in coefficients and in forecasting models. In extreme, DMMA even accommodates constant coefficients and equal model weights. Our approach, therefore, incorporates information from several combination methods in the frequentist area, such as equal model weights, as well as in the Bayesian area, such as BMA and DMA, using individual dynamic linear models. Thus, locally appropriate coefficients and forecasting models can be flexibly exploited over time.

Our contribution goes further than developing a new DMMA and comparing its out-of-sample performances to alternative models. The added flexibility of the DMMA approach allows us to more broadly analyze what specifically leads to forecasting improvements. We investigate whether forecast improvements are due to different predictors, different degrees of time variation in coefficients and in forecasting models. To that end, prediction variance is decomposed into five parts: (i) uncertainty caused by random fluctuations in data (*observational variance*), (ii) uncertainty due to coefficient estimation error (*estimation risk*), (iii) model uncertainty with respect to predictor selection, (iv) model uncertainty regarding the degree of time variation in coefficients, (v) model uncertainty in terms of the magnitude of time variation in forecasting models. To the best of our knowledge, this is the first work that systematically examines asset return predictability in each of these five respects.

Methodologically, the paper most similar to this chapter is Dangl and Halling (2012), which studies the importance of time-varying coefficients in predictive regressions. However, our work is different from theirs in several regards. First, we examine whether different degrees of time-variation in coefficients and in forecasting models matter. Our DMMA model nests the time-varying coefficients with BMA combination method used in Dangl and Halling (2012) and is advantageous in embedding the locally proper degree of time variation in forecasting models at each point in time. Moreover, we not only consider

the macroeconomic predictors emphasized by Dangl and Halling (2012), but also the technical indicators used by Neely et al. (2014), to provide additional information about the stock market. Besides, we allow for stochastic volatility instead of the constant volatility employed in Dangl and Halling (2012), which accommodates the widely identified fat tail property of financial data. Finally, compared with Dangl and Halling (2012), one more element of model uncertainty is added: uncertainty with regard to different choices of time variation in forecasting models, and we study what leads to forecast improvements according to different sources of uncertainty.

The most important result is that our approach of dynamic mixture model averaging (DMMA) outperforms the historical mean (HM), with positive out-of-sample  $R^2$  and large utility gains relative to HM for a mean-variance investor across different sample periods. Besides, DMMA also dominates alternative model combination methods, including equal weights, BMA and DMA, in terms of point forecast accuracy. With respect to different predictor sets, macroeconomic variables perform well for the whole sample period while technical indicators has better predictive performance for the recent subsample, and combining individual predictors within the same predictor sets improves the forecasting results.

Via the variance decomposition of prediction uncertainty, we find that DMMA effectively adapts the pattern in the stock market by detecting locally appropriate degree of time-variation in coefficients and in forecasting models, leading to mitigation of estimation risk and forecasting improvements.

Linking DMMA's predictability to the business cycle, the obtained results show that DMMA has superior out-of-sample performances during recessions compared to expansions, consistent with the asset pricing literature (Fama and French (1989), Campbell and Cochrane (1995), Cochrane (1999, 2005), Rapach

et al. (2010), and Dangl and Halling (2012)). Interestingly, while DMMA performs much better during recessions, simple models have slightly better out-of-sample results during expansions. This may be due to the fact that more sophisticated time varying models like DMMA are able to quickly adjust in times of stress, whereas, simple models are too static during recessions, but appropriate during economic recoveries.

The rest of this chapter is constructed as follows. Section 2.2 sets out the econometrics framework used in this work. Section 2.3 presents the predictors and priors used in the study. Empirical results are shown in Section 2.4, followed by the conclusion in Section 2.5.

## **2.2 Econometrics Framework**

In this section we set out our approach to excess return prediction, while taking three dimensions of model uncertainty into account: different predictor selection, different degrees of time variation in coefficients, and in forecasting models at each forecasting point. In Section 2.2.1, we demonstrate a dynamic linear model which allows for time-varying coefficients for a certain choice of predictors. In Section 2.2.2, we construct the dynamic mixture model averaging method to attach posterior probabilities to individual dynamic linear models, using different degrees of time variation in forecasting models.

### **2.2.1 Dynamic Linear Model**

Consistent with the majority of research on stock return prediction, we assume a linear prediction model.<sup>3</sup> In addition, our model also allows for time variation in the coefficients of the prediction model. With respect to the

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<sup>3</sup>See Avramov (2002), Cremers (2002), Andrew and Geert (2007), Welch and Goyal (2008), Dangl and Halling (2012), and Joscha and Schüssler (2014), among others.



time-varying coefficients specification, we assume it to follow a random walk process, signalling that changes in coefficients are unpredictable. As Dangl and Halling (2012) acknowledge, by reducing estimation errors and calibrating coefficients to observed data, random-walk coefficients have better out-of-sample performances compared to autocorrelated coefficients.<sup>4</sup> Note that our prediction and out-of-sample performance are in real time: we only use information at or before time  $t - 1$  if we aim to predict the excess stock return at  $t$ .

Assume  $r_t$  as the excess stock return at time  $t$ ,  $X_{t-1}$  as the specific predictor for each individual model at time  $t-1$ . The predictive model with time-varying coefficients is conducted on a monthly basis and can be represented as:

$$r_t = X_{t-1}\theta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t) \quad (\text{observation equation}) \quad (2.1)$$

$$\theta_t = \theta_{t-1} + u_t, \quad u_t \sim N(0, Q_t) \quad (\text{transition equation}) \quad (2.2)$$

where  $\theta_t$  is the coefficient vector that follows a random walk process, the errors  $\varepsilon_t$  and  $u_t$  are normally distributed with zero mean and uncorrelated across all lags with time-varying variances  $H_t$  and  $Q_t$ , respectively. We refer to  $H_t$  as the observational variance. Let  $X_{t-1} = [1, x_{t-1}]$ , where  $x_{t-1}$  is the predictor we choose at time  $t - 1$ . Therefore, dynamic linear models differ with respect to the choice of predictors. In Section 2.3.1, we discuss the set of predictors in  $x_t$ .

Given that we take a Bayesian perspective, denote  $D_t = [r_t, r_{t-1}, \dots, X_t, X_{t-1}, \dots]$  as the information set available at  $t$ , which includes all the previous information about excess stock return values, predictor values, as well as the priors for coefficients  $\theta_0$  and observational variance  $H_0$ . Essentially, we use a simple Kalman filter, to incorporate forgetting factors into the evolution of the parameters following Raftery et al. (2010) and Koop and Korobilis (2012). To explain

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<sup>4</sup>We further check this hypothesis in Appendix A.6 and find that random-walk coefficients dominate those with autocorrelated coefficients.

how this works, start with the standard Kalman filter. We obtain the posterior distribution for  $\theta_{t-1}$  as  $u_t$  follows a normal distribution with mean zero and covariance  $Q_t$ :

$$\theta_{t-1}|D_{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}) \quad (2.3)$$

The Kalman filter predicts  $\theta_t$  conditional on the information up to time  $t - 1$ :

$$\theta_t|D_{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t|t-1}) \quad (2.4)$$

where the estimated coefficients vector is  $\hat{\theta}_{t-1}$  and variance-covariance matrix of the coefficients is given by:

$$\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t \quad (2.5)$$

Raftery et al. (2010) and Koop and Korobilis (2012) suggest using a form of forgetting to ease computational demands instead of specifying the matrix  $Q_t$ . In particular, Equation (2.5) is replaced by:

$$\Sigma_{t|t-1} = \frac{1}{\lambda} \Sigma_{t-1|t-1}, \quad 0 < \lambda \leq 1 \quad (2.6)$$

or, equivalently,

$$Q_t = (\lambda^{-1} - 1) \Sigma_{t-1|t-1} \quad (2.7)$$

where  $\lambda$  is the forgetting factor. Therefore, according to Equation (2.7), the forgetting factor  $\lambda$  is essential in influencing the degree of time variation in coefficients, which can be interpreted as the age-weights for different time points. Constant coefficient models correspond to  $Q_t = 0$  and  $\lambda = 1$ . In cases where  $\lambda < 1$  imply that  $Q_t > 0$ , thus, the covariances  $\Sigma_{t|t-1}$  increase over time and coefficients are time-varying. The lower the value of  $\lambda$ , the more abrupt the coefficients change.  $\lambda$  has a substantial influence on coefficient stability and different degrees of  $\lambda$  lead to different dynamic linear models. In Appendix A.1, we provide details on the implementation of the dynamic linear models and the specification of time-varying volatility.

### 2.2.2 Dynamic Mixture Model Averaging

We argue above that different predictors and degrees of time variation in coefficients may influence our ability to forecast stock returns. Improper model selection can increase total variance of return prediction and affect the accuracy of statistical inference. However, one particular specification from the substantial pool of possibilities is unlikely to dominate all others at each point in time. Given a single model may not be systematically the most successful at prediction, one potential approach is to take model uncertainty into account and compare all the models simultaneously. This paper proposes the dynamic mixture model average (DMMA) approach which begins by allowing for possible degrees of time-varying coefficients and model weights, based upon their past forecasting performances. Using a Bayesian approach, the data identifies the precise degree of time variation in coefficients and forecasting models by attaching posterior weights to possible models. This flexibility allows us to detect locally appropriate models over time.

We can elucidate on the number of models our DMMA approach utilises, and compare it to DMA, by identifying the following parameters. Denote  $k_i$  as a choice of predictors from  $K$  candidates,  $\lambda_j$  as a choice of the degree of time-variation in coefficients from  $d$  candidates,  $\alpha_z$  as a choice of the degree of time-variation in coefficients from  $a$  candidates ( $i = 1, \dots, K; j = 1, \dots, d$  and  $z = 1, \dots, a$ ). Then, there are  $d \cdot K$  possible dynamic linear models and  $a$  different ways of combining them. Consequently, the predictive density of individual models and final forecasting results depend on the selection of predictors ( $k_i$ ), degrees of time variation in coefficients ( $\lambda_j$ ) and degrees of time variation in forecasting models ( $\alpha_z$ ) as well. Importantly, if the choices of  $\lambda_j$  and  $\alpha_z$  are fixed over time, DMMA shrinks to DMA.

According to Koop and Korobilis (2012), the prediction equation for different variables can be written in the form of conditional predictive density and the predictive weight attached to each variable  $k_i$  is:

$$\begin{aligned}
P(L_t = k_i \mid \lambda_j, \alpha_z, D_{t-1}) &\propto [P(L_{t-1} = k_i \mid \lambda_j, \alpha_z, D_{t-2})P(r_{t-1} \mid L_{t-1} = k_i, \lambda_j, \alpha_z, D_{t-2})]^{\alpha_z} \\
&= \prod_{s=1}^{t-1} \{[P(r_{t-s} \mid L_{t-s} = k_i, \lambda_j, \alpha_z, D_{t-s-1})]^{\alpha_z}\}^s
\end{aligned} \tag{2.8}$$

where  $L_t$  represents the predictor  $k_i$  selected, given the degree of time-variation in coefficients  $\lambda_i$  and time-variation in forecasting models  $\alpha_z$  at time  $t$ .<sup>5</sup> Here  $\alpha_z$  is the other forgetting factor ( $0 \leq \alpha_z \leq 1$ ). We use  $s$  as the exponential power of the predictive distribution in Equation (2.8). When  $s = t - 1$ , we obtain  $\{P(r_1 \mid L_1 = k_i, \lambda_j, \alpha_z, D_0)^{\alpha_z}\}^{t-1}$ , which means that the predictive distribution at time 1 is largely discounted, as it is distant from time  $t$ . Whereas, when  $s = 1$ ,  $P(r_{t-1} \mid L_{t-1} = k_i, \lambda_j, \alpha_z, D_{t-2})^{\alpha_z}$ . This indicates that the more recent predictive density will obtain larger weight compared to the more distant ones, where the exact dynamics is controlled by the forgetting factor  $\alpha_z$ . We specify possible values of  $\lambda_j$  and  $\alpha_z$  in Section 2.3.2.

Interestingly, focusing on Equation (2.8), some conventional models are nested in DMMA. When models are equally weighted, that is the time variation in models  $\alpha = 0$ , forecasting models are constant over time. Huang and Lee (2010) advocate an approach with equal weights which dominates other forecasting methods, using equity premium prediction as an example. Similarly, Rapach et al. (2010) demonstrate the superior out-of-sample equity premium prediction of the combination method with equal weights. When  $\alpha = 1$ , there is no discounting, and therefore, no role for  $\alpha$ , model averaging shrinks to normal BMA, which is widely used in the stock return prediction literature, see e.g., Avramov (2002), Cremers (2002), Dangl and Halling (2012), and

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<sup>5</sup>Equation (2.8) can be derived based on Equation (A.17) and (A.18) in Appendix A.2.

Turner (2015). However, it does not distinguish between forecast performance in the recent past and more distant past. Even if we employ recursive forecasting using BMA and incorporate some time variation in the forecasting model, posterior model probabilities will only vary slightly as new data is incorporated. When  $\alpha < 1$  and is fixed over time, DMMA shrinks to DMA, which depends more on the recent forecast performance. If a certain value is allowed for  $\alpha$ , it might only be locally suitable and the model can be misspecified. Our DMMA framework makes the model averaging process become as flexible as possible and allows data to detect appropriate models by considering different degrees of  $\alpha$ .

The posterior probability of each  $a \cdot d \cdot K$  specification is updated according to Bayes' rule. In Appendix A.2, we provide more details about dynamic mixture model averaging.

## 2.3 Empirical Study Design

### 2.3.1 Data Description

We examine stock predictability using monthly S&P 500 index excess returns, and in particular the difference between monthly return on the stock market and the risk-free rate. The choice of predictors is guided by the literature. A large number of research papers rely on macroeconomic predictors to forecast equity premium, while paying little attention to technical indicators. Neely et al. (2014), however, address the fact that macroeconomic predictors and technical indicators provide complementary information in terms of improving forecast accuracy and economic gains. We, therefore, consider both macroeconomic and technical predictors within our model combination with dynamic linear models.

The macroeconomic predictors we apply are the most widely used in empirical excess returns models.<sup>6</sup> The data set is from Welch and Goyal (2008).<sup>7</sup> Table 2.1 provides a short description of 12 macroeconomic predictors for the sake of brevity (see Welch and Goyal (2008) for details).<sup>8</sup> Following Neely et al. (2014), we also construct 14 technical predictors based on three strategies: moving-averages (MA), momentum (MOM) and volume (VOL). Table 2.1 illustrates the macroeconomic and technical predictors we consider.<sup>9</sup> With respect to technical indicators,  $MA(s, l)$  generates a buy signal if the stock price in the short( $s$ ) MA is larger than that in the long( $l$ ) MA ( $s = 1, 2, 3$  and  $l = 9, 12$ ).  $MOM(m)$  shows a positive momentum effect if the current price is larger than the price  $m$  periods ago ( $m = 9, 12$ ).  $VOL(s, l)$  indicates a strong market trend if the recent stock market volume as well as the stock price increases, where  $s = 1, 2, 3$  ( $l = 9, 12$ ) controls the recent (distant) past. In sum, we employ 26 macro and technical predictors to predict equity premium,<sup>10</sup> and the full data set is from December 1950 to December 2015.<sup>11</sup>

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<sup>6</sup>Some powerful macroeconomic predictors are uncovered, including net payout yield (Boudoukh et al., 2007), investor sentiment aligned (Huang et al., 2015) and short interest (Rapach et al., 2016). All of them are suggested to have comparably good out-of-sample performances. However, in our work, we exclude these predictors due to data availability.

<sup>7</sup>The data is available from Amit Goyal's webpage at <http://www.hec.unil.ch/agoyal/>.

<sup>8</sup>Compared with Welch and Goyal (2008), we exclude quarterly observations, also the "dividend-to-price ratio" and "term spread" for collinearity reasons. "Cross-section premium" is also excluded as it is only available from May 1937 to December 2002. Whereas, except for "cross-section premium", all the other data can extend to a longer time period: January 1927 to December 2015.

<sup>9</sup>In Appendix A.3, further details about the construction of technical indicators are provided.

<sup>10</sup>If we consider all the models generated by the 26 predictors, there would be  $2^{26}$  model specifications, which would present excessive computational demands. Consequently, we consider single predictor in each regression as demonstrated in Section 2.2.

<sup>11</sup>Accordingly, if the training period is ten years, the sample period will start from November 1960. Choosing such a long period and omitting other predictors, our aim is to alleviate worries of sample selection bias for our results.

### 2.3.2 Prior Choices

The empirical method described in Section 2.2 requires appropriate priors and choices of time variation in coefficient ( $\lambda$ ) and in forecasting models ( $\alpha$ ). First, we suggest the prior of the coefficient  $\theta_0$  in the predictive regression in Equation (2.2) as:

$$\theta_0 \sim N(\hat{\theta}_0, \Sigma_{0|0}) \quad (2.9)$$

where  $\hat{\theta}_0$  is the OLS estimate of coefficients in the training period. Similarly, the variance-covariance matrix  $\Sigma_{0|0}$  is the corresponding OLS estimate of coefficients' covariance in the training period.<sup>12</sup>

Second, we need to choose a range of possible values of  $\lambda$  and  $\alpha$ , in other words, degrees of time varying coefficients and forecasting models. We consider  $\lambda \in [0.90, 0.95; 0.99; 1]$  and  $\alpha \in [0; 0.90; 0.95; 0.99; 1]$  for time variation in coefficients and forecasting models, which shall cover all reasonable values given monthly data.<sup>13</sup> To explain how it works, let us assume  $\lambda=0.99$  with monthly data. This implies that observations for the covariances of coefficients last year have approximately 89% as much weight as last month. This large  $\lambda$  would be the case when we have gradually changing coefficients. In contrast, when  $\lambda=0.90$ , the covariances of coefficients last year only have 28% as much weight as last month. Similarly, when  $\alpha=0.90$ , last year's forecast performance only receives 28% weight compared to that last month. The last two cases imply acute instability in financial markets and thus, are selected as the lower bounds (except equal weights with  $\alpha = 0$ ). Consequently, DMMA incorporates the cases from no changes to gradual and abrupt changes in coefficients and in forecasting models. Based on the range of time variation in coefficients

<sup>12</sup>We repeat the analysis using noninformative prior  $\theta_0 \sim N(0, \Sigma_{0|0})$  and obtain similar results.

<sup>13</sup>Dangl and Halling (2012) consider a more narrow range,  $\lambda \in [0.96; 0.98; 1]$ .  $\lambda, \alpha = 0.95$  or  $0.99$ , are the values allowed by Koop and Korobilis (2012) for DMA in an inflation prediction context.

and forecasting models, we then study which value of  $\lambda$  and  $\alpha$  is supported by the data.

As is common in the literature, we initially assign a diffuse conditional prior for different choices of predictor, different degrees of time variation in coefficients as well as in forecasting models, which means,  $P(\alpha_z | D_0) = 1/a = 1/5$ ,  $P(\lambda_j | \alpha_z, D_0) = 1/d = 1/4$  and  $P(k_i | \lambda_j, \alpha_z, D_0) = 1/K = 1/26$ . Therefore, each predictor and model specification have the same probability at the beginning.

## 2.4 Empirical Results

Our results section begins by examining whether out-of-sample predictability for stock returns is achieved by our dynamic mixture model averaging methodology. Next, we decompose the prediction variance and highlight the origins of the forecasting power of DMMA compared to alternative approaches. Finally, we link predictability to the business cycle.

### 2.4.1 Out-of-sample Predictability

We begin our formal analysis by comparing our DMMA with an historical mean (HM) model. Welch and Goyal (2008) indicate that HM can be a strict out-of-sample benchmark, which most predictors fail to outperform. Specifically, HM excludes predictors and only includes a constant term in the regressions, and is nested in our set of predictive regressions. Here we assume that the coefficient and volatility of HM are constant following previous studies (see Welch and Goyal (2008), Campbell and Thompson (2008), and Dangl and Halling (2012)).

Moreover, we consider the following models for comparison in Table 2.2:



- DMMA: Forecasts using dynamic mixture model averaging. We consider a variety of degrees of time variation in coefficients  $\lambda \in [0.9, 0.95; 0.99; 1]$  and in forecasting models  $\alpha \in [0; 0.90; 0.95; 0.99; 1]$ . DMMA nests all the following predictive models.
- EW: Forecasts using equal-weighted models with time-varying coefficients ( $\alpha = 0$ ).
- EW-CC: Forecasts using constant coefficients and equal weights ( $\lambda = 1$  and  $\alpha = 0$ ).
- BMA: Forecasts using Bayesian model averaging with time-varying coefficients ( $\alpha = 1$ ).
- BMA-CC: Forecasts using constant coefficients and Bayesian model averaging ( $\lambda = 1$  and  $\alpha = 1$ ).
- DMA: Forecasts using dynamic model averaging with time-varying coefficients and forecasting models ( $0 < \lambda < 1$  and  $0 < \alpha < 1$ ), where the degrees of time-variation in coefficients and forecasting models are fixed over time.
- HM: Forecasts using historical mean model without any predictors while keeping the coefficients and volatility constant ( $k = 0$  and  $\lambda = 1$ ).

Although DMMA is flexible enough to nest alternative model specifications, our goal is not to construct the most general model specification. Rather, we aim to incorporate a number of features that may be essential for forecast accuracy and portfolio allocation, including multiple predictors, time-varying volatility, time-evolving coefficients and time-evolving forecasting models.

Note that as out-of-sample predictability can be spurious and driven by some outliers, it would be unreasonable to focus on only one sample period.

Hence, in light of the analysis from Dangl and Halling (2012), we study three different sample periods beginning in three different years (1960+, 1976+ and 1988+) to confirm our results.<sup>14</sup> The literature has suggested that out-of-sample stock return predictability is mainly driven by exceptional periods such as the oil price shock in 1975 and the stock market crash in 1987.<sup>15</sup> To get rid of the disturbances of distress, two subsamples begin from 1976 and 1988, respectively.

#### 2.4.1.1 Statistical Evaluation

We use the out-of-sample  $R^2$  ( $R_{OS}^2$ ), Clark and West (2007) statistics and model predictive log likelihoods for different subsamples to statistically evaluate our model's out-of-sample predictability. In detail, the first statistic,  $R_{OS}^2$ , as acknowledged by Campbell and Thompson (2008), is the fractional reduction in mean squared forecast error (MSFE) for the predictive model compared to HM benchmark:

$$R_{OS}^2 = 1 - \frac{\sum_{t=\underline{t}}^{\bar{t}} (r_{t+1} - \hat{r}_{t+1})^2}{\sum_{t=\underline{t}}^{\bar{t}} (r_{t+1} - \bar{r}_{t+1})^2} \quad (2.10)$$

where  $\underline{t}$  is the starting of the evaluation period,  $\bar{t}$  is the end of the evaluation period,  $\hat{r}_{t+1}$  is the estimated prediction from a regression using the information at time  $t$  and  $\bar{r}_{t+1}$  denotes the estimated HM at time  $t$ . If  $R_{OS}^2 > 0$ , MSFE of the predictive regression is smaller than that of HM, thus,  $\hat{r}_{t+1}$  has more accurate prediction than  $\bar{r}_{t+1}$ .

The second measurement we report is the widely used Clark and West (2007) test (CW), which evaluates the statistical differences in forecasts.<sup>16</sup> The

<sup>14</sup>We start from 1960 to have 10 years training periods.

<sup>15</sup>See, for example, Welch and Goyal (2008), Rapach et al. (2010), Dangl and Halling (2012), and Rapach et al. (2010).

<sup>16</sup>The CW test adjusts MSFE, to account for the noise in the forecasts brought by the larger and complex model.

advantage of the CW test is that it still follows an asymptotically standard normal distribution when comparing to the forecasting results of nested models. This is exactly our case as HM is nested in our general DMMA framework. The CW statistic tests the null hypothesis that the MSFE of HM is less than or equal to that of the predictive regression. The upper tail alternative hypothesis of the CW test is that the MSFE of HM is greater than that of the predictive regression.

The third statistical criteria we use to assess our models is the log predictive likelihood ( $\text{Log}(PL)$ ). Since it involves the entire predictive distribution, the log predictive likelihood is a frequently used evaluation method for Bayesian models (Geweke and Amisano, 2011). The larger the log predictive likelihood, the better the forecasts in a Bayesian comparison.

Table 2.3 presents the first set of core statistical results from our empirical analysis.<sup>17</sup> The overall story is clear: DMMA outperforms HM for all subsample periods using different statistical evaluations. Moreover, DMMA has better results than other model combination methods including equal-weighted models (EW), Bayesian model averaging (BMA), and dynamic model averaging (DMA), in terms of point forecast accuracy.

We first examine dynamic mixture model averaging's performances in greater detail compared to the benchmark historical mean in Table 2.3. DMMA takes all sources of model uncertainties into account, allowing for different choices of predictors, varying degrees of coefficient and forecasting models adaptivity. We find that DMMA consistently outperforms HM, with  $R_{OS}^2$  larger than zero and substantially larger log likelihoods than HM across three different sample periods. The conclusion that DMMA has statistically lower forecast errors than HM is confirmed by the Clark and West test. It is worth noting

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<sup>17</sup>Our baseline results are based on the one-month ahead forecast and we further present forecast results for longer horizon in Appendix Table A.7.

that DMMA's out-of-sample statistical performances slightly worsen during the period 1976+ and period 1988+. This is consistent with the finding that prediction accuracy for forecasting excess stock returns may be driven, for example, by the oil price shock in 1973-1975 and the stock price crash in 1987 (see Campbell and Thompson (2008), Dangl and Halling (2012), and Joscha and Schüssler (2014)). However, DMMA still outperforms HM for sample periods 1976+ and 1988+, signalling that our framework is robust to different sample periods.

Next, we study the models that are nested in DMMA and examine which feature leads to forecasting improvements. In particular, we present the results for EW, BMA, and DMA we built on, in Panel B, C and D of Table 2.3 respectively. Looking at the results for EW in Panel B, we find that the simple combination method performs reasonably well. This may be somewhat unsurprising since a model with equal weights is a challenging benchmark in the forecasting combination literature (Rapach et al. (2010), Huang and Lee (2010), and Geweke and Amisano (2012)). We further study how time-varying coefficients influence the results.  $R_{OS}^2$  for constant coefficient with equal model weights (EW-CC) deteriorates compared to time-varying coefficients with EW, confirming the finding in the literature that parameter instability matters for return predictability.

Turning to Table 2.3 Panel C, we investigate Bayesian model averaging's (BMA) ability to predict stock returns. Interestingly, we find BMA does not outperform HM for our dataset. Geweke and Amisano (2012) suggest that the condition of BMA on "one of the models under consideration being true" seems inappropriate especially for the sporadically volatile stock market. DMMA, however, detects the locally appropriate time variation in coefficient and in forecasting model at each point in time and assigns different weights to these combination methods, according to their past forecast performance. Therefore,

it is reasonable that DMMA improves upon models with EW and models with BMA with regard to  $R_{OS}^2$ .<sup>18</sup>

Last but not least, we employ alternative specifications of dynamic model averaging in Panel D of Table 2.3, in which we assume that coefficients and forecasting models change in the same fashion over time. None of the DMAs have positive  $R_{OS}^2$  and  $p$  values less than 10% for the CW test. Data prefers gradual changes in forecasting models, as the DMAs with  $\alpha = 0.9$  are much worse than the ones with  $\alpha = 0.99$ , indicating the importance of choosing the exact time variation in forecasting models. This further confirms that even if we take time-varying coefficients and forecasting models into account, predictability can still disappear if we ignore the importance of evolving degrees of coefficients and models adaptivity.

We employ two sets of predictors: macroeconomic and technical predictors to capture the economic and trading patterns. It would be interesting to see which sets of the predictors perform better and whether their predictive power is complimentary. Table 2.4 presents the results for our DMMA method and other nested models using different sets of predictors. Using macroeconomic and technical indicators individually, DMMA still outperforms HM and has the highest out of sample  $R_{OS}^2$  consistently compared to EW, EW-CC, BMA and BMA-CC.<sup>19</sup> This is consistent with the baseline results. Macroeconomic predictors forecast stock returns well for the whole sample period 1960+, with  $R_{OS}^2$  up to 2.04%. Technical indicators, on the other hand, predict slightly well compared to macroeconomic variables for subsamples 1976+ and 1988+. As designed for analyzing short-term price movements, technical indicators are used extensively by traders in the market especially during recent decades.

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<sup>18</sup>Even though occasionally, DMMA has slightly smaller predictive likelihoods than EW and EW-CC, the improvements of DMMA in terms of  $R_{OS}^2$  is huge.

<sup>19</sup>The analysis of DMA models for different predictor sets is not included, as DMA cannot beat HM in Table 2.3. Detailed results for this specific case will be provided upon request.

Combining technical indicators and macroeconomic variables leads to better (see period 1976+) or slightly worse forecasts than the best alternative.

Table 2.5 further shows the results based on the 26 univariate models including or excluding time-varying coefficients. For comparison, the results of each predictor set as a whole are also presented. We uncover a significant improvement in predictive power after including time-varying coefficients in almost all the cases, suggesting the importance of taking parameter instability into account when forecasting stock returns. Several macroeconomic variables such as dividend-price ratio (dy), earnings-price ratio (ep) and treasury bill rate (tbl) forecast well for the whole sample period 1960+, with  $R_{OS}^2$  at least 1.39%. For the subsample period of 1988+, however, individual technical indicators outperform macroeconomic predictors. Interestingly, combining univariate models within each predictor set enhances prediction accuracy. Nevertheless, as suggested by Table 2.4, applying both technical and macroeconomic variables is not necessary to improve forecasting results for each subsample period. This may due to the fact that technical indicators usually provide buy or sell signals and their data types are different from those of macroeconomic variables that reveal economic fundamentals. DMMA does a better job extracting information from the same predictor category than combining different sets of predictors together.

All in all, the DMMA method we propose in this work provides improved statistical performance compared to historical mean, equal weights, Bayesian and dynamic model averaging across different subsample periods in terms of out-of-sample  $R^2$ . By detecting the locally appropriate degree of time variation in coefficients and forecasting models, DMMA can predict with misspecified models and quickly adapt the dynamics in the data generating process.<sup>20</sup> In

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<sup>20</sup>Raftery et al. (2010) show that DMA rapidly accommodates changes in coefficients and changes in the entire forecasting models, by employing a simulation study. DMMA offers greater flexibility than DMA, and is capable to detect changes in the stock market.

Section 2.4.2, we decompose the prediction variance and further explore the reason why DMMA outperforms other Bayesian methods, such as BMA and DMA. With respect to parameter instability, time-varying coefficients plays an important role in predictive regressions, similar to Dangl and Halling (2012). By studying macroeconomic and technical predictors individually and employing univariate analysis, we find that macroeconomic variables forecast well for the whole sample period but technical indicators outperform macroeconomic predictors in the recent subsamples, and combining different predictors within the same predictor set (macroeconomic or technical) improves forecast accuracy. We further investigate the reason why DMMA outperforms BMA and DMAs via variance decomposition in Section 2.4.2.

#### 2.4.1.2 Economic Evaluation

In the previous section we suggest that out-of-sample  $R_{OS}^2$  can be obtained using DMMA to predict stock returns, but is this meaningful for investors and traders? In other words, we have indicated that our approach has statistical meaning but does it provide economic value?

To answer this question, we report the certainty equivalent return ( $CER$ ) for a mean-variance risk-averse investor, who allocates his wealth between equities and risk-free assets using forecasting results from our variance models. The expected utility  $U(R_p)$  for this mean-variance investor is:

$$U(R_p) = E(R_p) - \frac{1}{2}\gamma Var(R_p) \quad (2.11)$$

where  $R_p$  is the investors' portfolio return,  $E(R_p)$  is the expected value of the return,  $Var(R_p)$  is the variance of the return and we define the variance parameter  $\gamma = 3$ .<sup>21</sup> At the end of  $t$ , the investor optimally allocates a portfolio

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<sup>21</sup> $\gamma = 3$  is a standard setting in the literature, see Neely et al. (2014). We repeat same analysis for  $\gamma = 5$ . Similar results are obtained.

weight in the risky asset:

$$w_t = \frac{1}{\gamma} \frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2}$$

where  $\hat{r}_{t+1}$  is the forecast of excess stock return and  $\hat{\sigma}_{t+1}^2$  is the forecast of its variance. Following Campbell and Thompson (2008) and Neely et al. (2014), we limit the percentage invested in equities to be between 0% and 150% and assume that a five-year moving window of past returns is used to estimate the variance forecasts.

Finally, the *CER* for the portfolio is:

$$CER_p = \hat{\mu}_p - \frac{1}{2}\gamma\hat{\sigma}_p^2 \quad (2.12)$$

where  $\hat{\mu}_p$  and  $\hat{\sigma}_p^2$  are the mean and variance for the investor's entire portfolio over the sample period. Monthly *CER* is annualized by multiplying by 1200. Moreover, we consider the effect of transaction costs in *CER* following Balduzzi and Lynch (1999) and Neely et al. (2014), where the costs are measured using the percentage change of wealth traded each month and assuming a proportional transactions cost equal to 50 basis points per transaction.

Table 2.6 shows the certainty equivalent return (*CER*) and the Sharpe Ratio (*SR*) for different models over different sample periods. The conclusion that DMMA has superior forecasts than HM is confirmed and strengthened using the economic criteria. Relative to other approaches, DMMA has good economic performances, and is at least comparable to the best alternative. For instance, DMMA outperforms EW economically in the subsample 1988+ and is close to the results of it for the rest of sample periods. DMAs with moderately changing coefficients and forecasting models obtain high *CERs* in the period 1988+, however, they cannot outperform HM statistically.<sup>22</sup> We propose that

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<sup>22</sup>This is consistent with the finding of Cenesizoglu and Timmermann (2012) who suggest that there is a weak link between point forecast accuracy (e.g. out-of-sample  $R^2$ ) and economic value.



DMMA is the best among all the models we consider, considering both statistical and economic perspectives. The results of economic evaluation for different sets of predictors and univariate models are presented in Appendix A.4.

## 2.4.2 Sources of Prediction Uncertainty

Our study is innovative not only because our DMMA approach outperforms the historical mean statistically and economically, but also forecast errors beyond the standard approach can be delineated. This means that the relative importance for predictors, time-varying coefficients, and the individual model weights can be tracked over time. In this framework, the prediction variance of the excess stock return can be decomposed. We, therefore, are able to understand our model's underlying features and the source of forecasting power. This constitutes one of the critical contributions of this work.

We begin with the decomposition about different variabilities in models  $\alpha_z$ , based on the *Law of Total Variance*, prediction variance can be written as:

$$Var(r_t) = \mathbb{E}_{\alpha_z}(Var(r_t | \alpha_z)) + Var_{\alpha_z}(\mathbb{E}(r_t | \alpha_z)) \quad (2.13)$$

where  $\mathbb{E}_{\alpha_z}$  and  $Var_{\alpha_z}$  are the expectation and prediction variance with regard to  $\alpha_z$ . We further decompose  $Var(r_t | \alpha_z)$  in Equation (2.13) regarding the time variation in coefficients  $\lambda_j$  into:

$$Var(r_t | \alpha_z) = \mathbb{E}_{\lambda_j}(Var(r_t | \lambda_j, \alpha_z)) + Var_{\lambda_j}(\mathbb{E}(r_t | \lambda_j, \alpha_z)) \quad (2.14)$$

Similarly, given different choices of predictors  $k_i$ ,  $Var(r_t | \lambda_j, \alpha_z)$  in Equation (2.14) can be written as:

$$Var(r_t | \lambda_j, \alpha_z) = \mathbb{E}_{k_i}(Var(r_t | k_i, \lambda_j, \alpha_z)) + Var_{k_i}(\mathbb{E}(r_t | k_i, \lambda_j, \alpha_z)) \quad (2.15)$$

Finally, substitute Equation (2.15) and (2.14) into (2.13), we obtain:

$$\begin{aligned}
Var(r_t) &= \mathbb{E}_{k_i, \lambda_j, \alpha_z} [Var(r_t | k_i, \lambda_j, \alpha_z)] + \mathbb{E}_{\lambda_j, \alpha_z} \{Var_{k_i}[\mathbb{E}(r_t | k_i, \lambda_j, \alpha_z)]\} \\
&\quad + \mathbb{E}_{\alpha_z} \{Var_{\lambda_j}[\mathbb{E}(r_t | \lambda_j, \alpha_z)]\} + Var_{\alpha_z}[\mathbb{E}(r_t | \alpha_z)] \\
&= \sum_{\alpha_z} \{ \sum_{\lambda_j} [ \sum_{k_i} (H_t | k_i, \lambda_j, \alpha_z, D_t)] P(k_i | \lambda_j, \alpha_z, D_t) ] P(\lambda_j | \alpha_z, D_t) \} P(\alpha_z | D_t) \\
&\quad + \sum_{\alpha_z} \{ \sum_{\lambda_j} [ \sum_{k_i} (X_t \Sigma_{t+1|t} X_t' | k_i, \lambda_j, \alpha_z, D_t) P(k_i | \lambda_j, \alpha_z, D_t) ] P(\lambda_j | \alpha_z, D_t) \} P(\alpha_z | D_t) \\
&\quad + \sum_{\alpha_z} \{ \sum_{\lambda_j} [ \sum_{k_i} (\hat{r}_{t+1,i}^{j,z} - \hat{r}_{t+1}^{j,z})^2 P(k_i | \lambda_j, \alpha_z, D_t) ] P(\lambda_j | \alpha_z, D_t) \} P(\alpha_z | D_t) \\
&\quad + \sum_{\alpha_z} [ \sum_{\lambda_j} (\hat{r}_{t+1}^{j,z} - \hat{r}_{t+1}^z)^2 P(\lambda_j | \alpha_z, D_t) ] P(\alpha_z | D_t) \\
&\quad + \sum_{\alpha_z} (\hat{r}_{t+1}^z - \hat{r}_{t+1})^2 P(\alpha_z | D_t)
\end{aligned} \tag{2.16}$$

Hence, Equation (2.16) sheds light on the sources of uncertainty of return prediction. Intuitively, the first term captures the expected variance of the innovation term in the measurement equation, conditional on the choices of predictors  $k_i$ , degree of time variation in coefficients  $\lambda_j$  and forecasting model  $\alpha_z$ . We call it observational variance. The second term indicates the expected variance of errors in coefficients, which can be classified as estimation uncertainty in coefficients. Whereas, the remaining components of Equation (2.16) are referred to as model uncertainty. The third term characterizes model uncertainty with regard to predictor selection. The fourth term measures model uncertainty in terms of degree of time variation in the coefficients. Finally, the fifth term states model uncertainty regarding the degree of time variation in forecasting models. Dangl and Halling (2012) consider the first four sources of forecast errors. To the best of our knowledge, ours is the first work in the return predictability literature that investigates model uncertainty with respect to different choices of time variation in forecasting models.

Figure 2.1 depicts different sources of prediction variance for three Bayesian

approaches: (i) DMMA, (ii) BMA ( $\alpha = 1$ ) and (iii) DMA model (take  $\lambda = 0.9, \alpha = 0.9$  as an example).<sup>23</sup> Column (a) of Figure 2.1 shows the relative weights of observational variance (Obs.var.), uncertainty about estimating coefficients (Unc.coef.) and model uncertainty (Mod.unc.).<sup>24</sup> For all three approaches, DMMA, BMA and DMA, observational variance dominates in the sense that it is the most important source of prediction failure. Dangl and Halling (2012), claim that this is conventional for stock return prediction as random fluctuations are expected to cause considerable volatility, especially for the one month forecast horizon we consider. For DMMA and BMA, estimation risk and model uncertainty are small except for the initial data-points of the out-of-sample predictive process and the peak of model uncertainty during the financial crisis in 2008.<sup>25</sup> Whereas, for DMA, estimation uncertainty accounts for around 20% of the total prediction variance and model uncertainty is nonnegligible.

With respect to estimation uncertainty and variance caused by predictor selection in column (b) of Figure 2.1, there are notable differences among DMMA, BMA and DMA. Importantly, for DMMA, uncertainty regarding coefficient estimation accounts for the largest proportion in the initial data points, however, it is of less importance after 1965. In the meantime, uncertainty with regard to predictor selection becomes crucial. Whereas, when we fix time variation in the forecasting model using BMA, estimation uncertainty in coefficients dominates the remaining variance for most periods, only with occasional switches

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<sup>23</sup>We consider  $\lambda = 0.9, \alpha = 0.9$  because they represent extremely rapidly changing coefficients and forecasting models. Our aim is to demonstrate different sources of uncertainty when choosing inappropriate parameters.

<sup>24</sup>In terms of absolute values of different variances, DMA has the largest prediction variance. DMMA, in contrast, has the smallest variance. The detailed results will be provided upon request.

<sup>25</sup>As priors influence results in a Bayesian framework, Geweke and Amisano (2010) argue that it is reasonable for the prediction variance to be sensitive to the initial forecasting data-points. However, results will be invariant to the prior distribution after data has been accumulated.

to model uncertainty with respect to predictor selection. If the coefficient and forecasting models change in the same fashion over time (DMA), estimation risk is prominent at the start of the sample. These first imply that observational uncertainty, estimation uncertainty and uncertainty with respect to predictor selection are the top three sources of prediction variance that hinder forecasting performance for different models. Second, DMMA has the smallest estimation error among different alternatives, whereas, when we select an inappropriate degree of time variation in coefficients and in forecasting models, the estimation risk can be large.

Besides, turning to the rest of the model uncertainty in DMMA, we uncover that uncertainty regarding different choices of time variation in forecasting models is negligible after the initial 30 years, implying that learning the dynamics in the time-varying forecasting models can take some time. Uncertainty with regard to different choices of time variation in coefficients, however, is low except for the fluctuations around recessions (e.g., the post-Korean War recession between 1953-1954, the oil shock around 1973 and the financial crisis from 2007). Uncertainty with respect to predictor selection cannot be neglected. This implies that the ensemble of features of DMMA is necessary, including combining multiple predictors, allowing varying degrees of coefficients adaptivity and different degrees of time variation in forecasting models.

In spite of the fact that estimation uncertainty in coefficients is one of the key factors obstructing forecasting performance, our flexible DMMA model outperforms alternatives because it makes use of all the information in the dataset. In other words, our model effectively adapts the pattern in the unstable stock market by embedding the precise level of time variation in coefficients and forecasting models, thus, the variances due to uncertainty about the choice of time variation in coefficients and forecasting models are small. When comparing the differences of variance decomposition between BMA and

DMA, one possible explanation for DMMA's superior out-of-sample performance is that considering a reasonable range of time variation in coefficients increases coefficient variability. This shall consequently offset the loss in forecast accuracy caused by the second largest source of prediction variance: coefficients estimation uncertainty. In addition, by combining different combination methods, DMMA enhances model adaptability and quickly detects locally appropriate models, therefore, improves upon time-varying coefficients with BMA and further compensates the losses due to estimation risk.

### **2.4.3 Linking Predictability to the Business Cycle**

Previously, we provided evidence of statistical and economic stock return predictability of our DMMA model relative to others. We also analyze what leads to improvements in predictability by decomposing variance. In this section, we link DMMA's predictability to the business cycle.

Theoretically, excess stock returns predictability is closely related to the business cycle (Fama and French (1989), Campbell and Cochrane (1995), Cochrane (1999, 2005), and Rapach et al. (2010) and Dangl and Halling (2012)). Investors are more risk-averse during recessions, who, in turn, ask for much higher excess stock returns for risk compensation. As a consequence, the equity premium tends to decrease during expansions and increase during recessions. Local maxima of the equity risk premia often appears to be near business cycles troughs, whereas, local minima occurs near business cycles peaks (Fama and French (1989), Campbell and Cochrane (1995), and Cochrane (1999)). In this framework, DMMA's predictability would rise if it captures the business cycle (Rapach et al. (2010), Henkel et al. (2011), and Dangl and Halling (2012)).

Rapach et al. (2010) systematically and empirically study the linkage between prediction improvements and the business cycle. Similarly, they predict equity premium by combining individual predictive regression models and find that the combination method has superior out-of-sample prediction of excess stock returns which, in turn, better links to the business cycle when comparing to individual forecasts and the historical mean model. Rapach et al. (2010) argue that the reason why the historical mean model cannot capture business-cycle fluctuations is because it always produces a very smooth prediction, therefore, fails to incorporate macroeconomic information. With respect to the individual predictive regressions, they may contain false signals and exhibit implausible fluctuations. Compared to the model combination method used in Rapach et al. (2010), DMMA may be better suited to flexibly forecast returns in different economic environments.

We use the NBER recessions and expansions data to identify how closely the predictability of the DMMA model is linked to the business cycle. Table 2.7 reports two statistics: out-of-sample  $R^2$  ( $R_{OS}^2$ ) and  $CER$  gains ( $\Delta CER$ ) relative to the no-predictability benchmark during recessions and expansions over different sample periods for various predictive models. Out-of-sample  $R^2$  of DMMA is substantially larger during recessions than expansions. In terms of economic evaluation, DMMA illustrates its unique power to generate considerable returns especially in recessions, with  $CER$  gains during recessions approximately 41 times larger than that during expansions. The fact that predictability will rise during recessions is in line with the empirical evidence provided by Rapach et al. (2010), Henkel et al. (2011) and Dangel and Halling (2012). Researchers argue that this is because HM model overestimates the equity premium, therefore, suffers from huge losses particularly in recessions. Importantly, DMMA still has positive out-of-sample  $R^2$  and  $CER$  gains during expansions, which further confirms the strong predictability of DMMA.

Interestingly, although flexible models, such as DMMA, have superior predictive power especially during recessions, simple models such as constant coefficients with equal weights, perform slightly better during expansions. This may be due to the fact that complicated models are able to quickly adjust to change explicitly in times of market stress. In contrast, simple models are usually too static and over-optimistic to detect any variability, which in turn becomes beneficial during an economic recovery.

Next, we closely look at the equity premium predictions and portfolio weights of risky asset around turning points of the business cycle. Figure 2.2 Panel A shows the predicted equity premiums around peaks and troughs. Predictions from DMMA fit the theoretical pattern acknowledged by Cochrane (1999, 2005): the predicted equity premium increases at the end of recession, signalling greater risk-aversion during recessions. In addition, local minima seems to be around the peak. However, investors who believe in the HM model are over optimistic and predictions from HM are too smooth to capture the fluctuations around business-cycle turning points.

We also find that a mean-variance optimizer who relies on DMMA appears to time the stock market and seize investment opportunities well. In essence, investors employing DMMA pull out of the stock market rapidly when the recession starts, and gradually increase equity holdings towards the end of recession. Whereas, HM gives investors false signals, making them fail to withdraw money from the equity market at the beginning of a recession.

We conclude that predictions from the historical mean cannot capture the abrupt changes in the stock market and are less economically meaningful. The agreement between DMMA's predictions and the asset price theory suggested by Cochrane (1999, 2005) provides more economic insights of equity premium predictability.

## 2.4.4 Model Characteristics

### 2.4.4.1 Which Predictor is Important?

Given that there are 12 macroeconomic predictors and 14 technical predictors for excess stock return, it would be interesting to see which one is the most important and how a predictor evolves over time. We measure this by presenting the posterior inclusion probability for each predictor at each time, which can be obtained using DMMA. Following the econometric framework mentioned above, we know that our predictive models are constructed in a way that only a single predictor is included in each model, thus, the posterior inclusion probability for each predictor can be treated as the posterior model probabilities. Hence, if the posterior model probability for a model or the posterior inclusion probability for a variable is high, that model is likely to be the true model and that variable may play an important role in predicting excess stock returns.

Figure 2.3 presents the time-varying posterior probabilities for the 26 predictors. From the initial data points until 1975, the shifts between different predictors are occasional and mostly between macroeconomic predictors: treasury bill rate (tbl), default yield spread (dfr), book-to-market ratio (bm), dividend yield (dy) and net equity expansion (ntis). Especially, treasury bill rate (tbl) is highly informative for stock prediction during 1957 to 1967 and 1973 to 1975. This echoes the results from Table 2.4 and 2.5 that macroeconomic variables forecast well for the sample period 1960+. After 1975, however, technical indicators become essential and have the similar predictive power as macroeconomic indicators, with inclusion probabilities for different predictors all around 0.04, only with several spikes around the financial crisis in 2008 (e.g., see stock variance (svar), default yield spread (dfr), MA(1,12) and



MA(2,12) for examples). This hints at the view that DMMA attaches approximately equal weights to each predictor from 1975 to the end of the sample period, and is consistent with the finding acknowledged by Neely et al. (2014) that macroeconomic predictors and technical predictors have complementary information. Moreover, we find that none of the predictor's posterior probabilities consistently exceeds the prior of  $1/26$  over time. This confirms the result in section 2.4.2 that there is nonnegligible uncertainty about the best predictor. Under this condition, DMMA automatically detects the best predictor while attaching low posterior weight to the ones that perform poorly over time.

#### **2.4.4.2 Analysis of Different Degrees of Time Variation in Coefficients and in Forecasting Models**

The preceding results show that DMMA can adapt the pattern in data by embedding the exact level of time variation in coefficients and forecasting models. Next we demonstrate the empirical evidence for that.

We closely look at posterior probabilities for possible degrees of time variation in coefficients for DMMA in Figure 2.4. In general, models with constant coefficients and gradually changing coefficients are informative about the movements of equity premium. In contrast, models with sudden changes in coefficients lose data support at the beginning of the sample. Observations around the oil shock in 1975 and the financial crisis in 2008 enhance the occasional evidence in favor of time-varying coefficients, echoing the conclusion of the dominance of dynamic models over static models especially during economic downturns in Section 2.4.3.

Figure 2.5 presents the posterior probabilities of different degrees of time

variation in forecasting models. Models with equal weights ( $\alpha = 0$ ) outperform other situations such as BMA ( $\alpha = 1$ ), abruptly changing predictive density combination and a gradually changing predictive density combination after a period of adjustment until 1975. Whereas, BMA is favored by the data at the beginning of out-of-sample period, with its inclusion probability larger than prior 0.2 during 1960 to 1965 and spikes in 1967 and 1975. The dominance of a certain value of  $\alpha$  for a prolonged period is reflected in the negligible uncertainty with respect to the degree of time variation in forecasting models. In addition, high inclusion probability for equal-weighted models from 1975 is in line with the finding in Section 2.4.4.1: DMMA attaches similar weights to different predictors at the end of the sample.

## 2.5 Conclusion

The literature on stock return forecasting suggests that the out-of-sample predictability is erratic (Cooper and Gulen (2006), Andrew and Geert (2007), Campbell and Thompson (2008), Welch and Goyal (2008), Joscha and Schüssler (2014), and Turner (2015)). Even though occasionally predictive power is found, it seems to be specific to some predictors in some sample periods, signalling the presence of model instability and uncertainty. Some papers have attempted to take these issues into account (see Rapach et al. (2010), Dangel and Halling (2012), Billio et al. (2013), and Johannes et al. (2014)), however, there is no consensus on the exact degree of time variation in coefficients and the method to combine all the individual models using different predictors. In this paper, we solve these problems by constructing dynamic mixture model averaging (DMMA), which incorporates possible degrees of time variation in coefficients and in forecasting models. Especially, we encompass moderate to abrupt changes and even no-change in coefficients and forecasting models in

a sense that DMMA combines different model combination methods such as equal model weights, Bayesian model averaging (BMA), dynamic model averaging (DMA) based on dynamic linear models.

What we uncover is that DMMA model generates more accurate forecasts compared to the historical mean (HM) benchmark across different sample periods. These statistical gains also lead to superior economic profits for a mean-variance investor. Most importantly, in terms of point accuracy, DMMA dominates its nested model combination methods including BMA, DMA and equal-weighted models. Besides, we confirm that time-varying coefficients regressions outperform those with constant coefficients. In terms of different sets of the predictors, we find that macroeconomic variables perform well for the whole sample period, whereas the technical predictor set generates more robust statistical and economics gains in recent subsamples.

We further pin down the origins of forecasting improvements by tracking different sources of uncertainty in the predictive regressions. Besides the observational variance, uncertainty regarding the errors from estimating the coefficients and model uncertainty with respect to predictor selection are the key factors hindering forecast accuracy. Uncertainty about the degree of time variation in coefficients, whereas, is small and uncertainty regarding the degree of time variation in forecasting models is only notable at the initial data points. Essentially, DMMA successfully reduces uncertainty regarding estimation error compared to other predictive models. These all hint at the view that DMMA successfully adapts the pattern in the unstable stock market by embedding the precise level of time variation in coefficients and finding the proper combination method, leading to higher forecast accuracy.

Finally, the results show that DMMA's predictability is closely linked to the business cycle. DMMA's superior performance is mainly driven by recessions,

with better forecast results during recessions than during expansions. Interestingly, simple models such as constant coefficients with equal weights slightly outperform DMMA during expansions. This may be due to the fact that complicated dynamic models are able to rapidly adjust changes explicitly in the time of stress. Whereas, simple models are usually too static to detect any variability, which in turn, become beneficial during an economic recovery. Note that DMMA also outperforms HM during expansions, indicating DMMA's predictive power is robust to different periods of the business cycle. Consistent with the asset pricing theory acknowledged by Cochrane (1999), our methodology forecasts an increasing equity premium at the end of the recession and the investor who follows DMMA can better time the stock market. This provides more insights about DMMA's predictive power.

Overall, DMMA is a powerful approach to predict stock returns. Our findings not only shed light on the roles of different degrees of time variation in coefficients and in forecasting models, but also have essential implications for monitoring ups and downs of the business cycle.

TABLE 2.1: List of Predictors

<i>No.</i>	<i>Predictor ID</i>	<i>Description</i>
Macroeconomic Indicators		
1	dy	Dividend yield
2	ep	Earnings-price ratio
3	de	Dividend-payout ratio
4	svar	Stock variance
5	bm	Book-to-Market ratio
6	ntis	Net Equity Expansion
7	tbl	Treasury bill rate
8	lty	Long-term yield
9	ltr	Long-term return
10	dfy	Default Yield Spread
11	dfr	Default Return Spread
12	infl	Inflation
Technical Indicators		
1	MA(1,9)	Moving average strategy
2	MA(2,9)	
3	MA(3,9)	
4	MA(1,12)	
5	MA(2,12)	
6	MA(3,12)	
7	MOM(9)	Momentum strategy
8	MOM(12)	
9	VOL(1,9)	Volume strategy
10	VOL(2,9)	
11	VOL(3,9)	
12	VOL(1,12)	
13	VOL(2,12)	
14	VOL(3,12)	

*Notes:* This tables shows the description of macroeconomic and technical predictors. Data is from December 1950 to December 2015.

TABLE 2.2: Model Sets

<i>Model specification</i>	<i>Predictors</i>	<i>Coefficients</i>	<i>Forecasting models</i>
DMMA	-	-	-
EW	-	-	$\alpha = 0$
EW-CC	-	$\lambda = 1$	$\alpha = 0$
BMA	-	-	$\alpha = 1$
BMA-CC	-	$\lambda = 1$	$\alpha = 1$
DMA	-	$0 < \lambda < 1$	$0 < \alpha < 1$
HM	$k = 0$	$\lambda = 1$	-

*Notes:* The table shows the model set with imposed restrictions on choices of predictors, time variation in coefficients and time variation in forecasting models.  $k$  refers to the number of predictors,  $\lambda$  specifies the degree of time variation in coefficient and  $\alpha$  indicates the degree of time variation in forecasting model. (-) implies that no restrictions are imposed.

TABLE 2.3: Statistical Evaluation

Panel A: Dynamic Mixture Model Averaging (DMMA)						
	Period:1960+		Period:1976+		Period:1988+	
	$R_{OS}^2(\%)$	$Log(PL)$	$R_{OS}^2(\%)$	$Log(PL)$	$R_{OS}^2(\%)$	$Log(PL)$
DMMA	<b>1.72**</b>	<b>1141.70</b>	<b>0.91*</b>	<b>802.66</b>	<b>0.88*</b>	<b>573.13</b>
Panel B: Equal Weights (EW)						
EW ( $\alpha=0$ )	<b>1.44**</b>	<b>1142.80</b>	<b>0.88*</b>	<b>803.05</b>	<b>0.67</b>	<b>573.31</b>
EW-CC ( $\lambda=1, \alpha=0$ )	<b>0.92***</b>	<b>1141.00</b>	<b>0.75**</b>	<b>802.78</b>	<b>0.62*</b>	<b>573.52</b>
Panel C: Bayesian Model Averaging (BMA)						
BMA ( $\alpha=1$ )	-1.26*	<b>1133.30</b>	-2.23	<b>795.27</b>	-0.15	<b>571.08</b>
BMA-CC ( $\lambda=1, \alpha=1$ )	-1.01*	<b>1128.20</b>	-2.35	<b>793.53</b>	-0.24	<b>571.12</b>
Panel D: Dynamic Model Averaging (DMA)						
$\lambda=0.90, \alpha=0.90$	-10.07	<b>1092.70</b>	-8.83	<b>768.47</b>	-10.34	<b>547.14</b>
$\lambda=0.95, \alpha=0.90$	-10.60	<b>1091.10</b>	-9.41	<b>767.47</b>	-11.15	<b>546.34</b>
$\lambda=0.99, \alpha=0.90$	-11.71	<b>1091.00</b>	-10.00	<b>768.31</b>	-11.48	<b>547.33</b>
$\lambda=0.90, \alpha=0.95$	-6.18	<b>1115.40</b>	-5.67	<b>784.89</b>	-6.92	<b>559.32</b>
$\lambda=0.95, \alpha=0.95$	-6.52	<b>1114.10</b>	-6.12	<b>784.14</b>	-7.57	<b>558.79</b>
$\lambda=0.99, \alpha=0.95$	-6.32	<b>1113.40</b>	-5.89	<b>784.28</b>	-6.94	<b>559.29</b>
$\lambda=0.90, \alpha=0.99$	-0.39	<b>1136.50</b>	-1.03	<b>798.44</b>	-1.23	<b>569.43</b>
$\lambda=0.95, \alpha=0.99$	-0.53	<b>1135.60</b>	-1.16	<b>798.11</b>	-1.46	<b>569.17</b>
$\lambda=0.99, \alpha=0.99$	-0.54	<b>1133.80</b>	-1.13	<b>797.59</b>	-1.47	<b>569.04</b>
HM	0	128.56	0	293.27	0	304.43

Notes: Statistical predictability for different models using out-of-sample  $R^2$  ( $R_{OS}^2(\%)$ ), Clark and West test (\*, \*\* and \*\*\* show that the null hypothesis that the MSFE of HM is less than or equal to that of predictive model, is rejected at the 10%, 5% and 1% significance level, respectively) and predictive log likelihoods ( $Log(PL)$ ). We consider different model combination methods, including combination with equal weights (EW) in Panel B, Bayesian model averaging (BMA) in Panel C and also all the possible dynamic model averaging (DMA) models in Panel D. Bold font suggests the statistics of that predictive model is larger than the corresponding one of HM. Following Dangi and Halling (2012), we study three different evaluation periods: 1960+, 1976+ and 1988+.

TABLE 2.4: Statistical Evaluation Using Different Sets of Predictors

	Period:1960+		Period:1976+		Period:1988+	
	$R^2_{OS}(\%)$	$Log(PL)$	$R^2_{OS}(\%)$	$Log(PL)$	$R^2_{OS}(\%)$	$Log(PL)$
Panel A: Macroeconomic Predictors						
DMMA	<b>2.04***</b>	<b>1140.90</b>	<b>0.75*</b>	<b>801.61</b>	<b>0.74*</b>	<b>572.22</b>
EW	<b>1.89***</b>	<b>1140.40</b>	<b>0.74*</b>	<b>801.17</b>	<b>0.41</b>	<b>572.27</b>
EW-CC	<b>1.28***</b>	<b>1139.30</b>	<b>0.64*</b>	<b>801.03</b>	<b>0.11</b>	<b>572.64</b>
BMA	-1.48*	<b>1133.60</b>	-2.68	<b>794.83</b>	-0.41	<b>570.67</b>
BMA-CC	-1.24*	<b>1128.60</b>	-2.76	<b>792.64</b>	-0.40	<b>570.83</b>
Panel B: Technical Indicators						
DMMA	<b>0.60*</b>	<b>1141.20</b>	<b>0.80*</b>	<b>802.08</b>	<b>1.01**</b>	<b>574.44</b>
EW	<b>0.59*</b>	<b>1141.00</b>	<b>0.73*</b>	<b>802.12</b>	<b>0.87</b>	<b>572.38</b>
EW-CC	<b>0.35*</b>	<b>1140.50</b>	<b>0.59*</b>	<b>802.02</b>	<b>0.77</b>	<b>572.27</b>
BMA	<b>0.41*</b>	<b>1140.40</b>	<b>0.63</b>	<b>801.47</b>	<b>0.78</b>	<b>572.26</b>
BMA-CC	<b>0.34</b>	<b>1139.60</b>	<b>0.43</b>	<b>801.16</b>	<b>0.70</b>	<b>571.90</b>
Panel C: Macroeconomic Plus Technical Predictors						
DMMA	<b>1.72**</b>	<b>1141.70</b>	<b>0.91*</b>	<b>802.66</b>	<b>0.88*</b>	<b>573.13</b>
EW	<b>1.44**</b>	<b>1141.20</b>	<b>0.88*</b>	<b>803.05</b>	<b>0.67</b>	<b>573.31</b>
EW-CC	<b>0.92***</b>	<b>1141.00</b>	<b>0.75**</b>	<b>802.78</b>	<b>0.62*</b>	<b>573.02</b>
BMA	-1.26	<b>1133.30</b>	-2.23	<b>795.27</b>	-0.15	<b>571.08</b>
BMA-CC	-1.01	<b>1128.20</b>	-2.35	<b>793.53</b>	-0.24	<b>571.12</b>
HM	0.00	128.56	0.00	293.27	0.00	304.43

Notes : Statistical evaluation using different sets of predictors. We only use macroeconomic predictors in Panel A, only employ technical indicators in Panel B and combine all the predictors in Panel C. See more details about the statistical evaluation in Table 2.3.



TABLE 2.5: Statistical Evaluation of Single-Predictor Models Including or Excluding Time-varying Coefficients

Panel A: Macroeconomic Predictors						
	Models incl. TVar-Coeff			Models excl. TVar-Coeff.		
	1960+	1976+	1988+	1960+	1976+	1988+
dy	<b>1.67**</b>	<b>0.05</b>	<b>0.59</b>	<b>0.14**</b>	-1.59	-2.76
ep	<b>1.51**</b>	-0.17	<b>0.09</b>	0.81	-1.12	-0.71
de	-0.19*	<b>0.08</b>	<b>0.26</b>	-1.34	-2.00	-2.97
svar	-1.39	<b>0.80</b>	<b>0.70</b>	-0.59	<b>0.49</b>	<b>0.35</b>
bm	<b>0.57</b>	<b>0.43</b>	<b>0.29</b>	-1.84	-1.11	-0.49
ntis	<b>0.83**</b>	<b>0.24*</b>	-0.63	-1.29	-0.45	-1.86
tbl	<b>1.39**</b>	-3.87	0.00	-5.07*	-5.97	-1.27
lty	-2.81*	-2.30	<b>0.07</b>	-4.42*	-3.44	-0.16
ltr	<b>0.69**</b>	<b>0.85*</b>	<b>0.30</b>	-0.11**	-1.36	-0.36
dfy	-0.62	-1.00	-1.01	-0.60	-0.51	-0.47
dfr	<b>0.46*</b>	-1.10	-1.52	-1.14	-0.87	-0.07
infl	-0.13	-0.77	-1.07	-0.36	-0.73	-1.09
DMMA	<b>2.04***</b>	<b>0.75*</b>	<b>0.74</b>	<b>1.04**</b>	<b>0.55*</b>	<b>0.44</b>
Panel A: Technical Indicators						
	Models incl. TVar-Coeff			Models excl. TVar-Coeff.		
	1960+	1976+	1988+	1960+	1976+	1988+
MA(1,9)	<b>0.45*</b>	<b>0.58</b>	<b>0.90**</b>	<b>0.20</b>	<b>0.32</b>	<b>0.82*</b>
MA(2,9)	<b>0.53</b>	<b>0.49</b>	<b>0.85*</b>	<b>0.41*</b>	<b>0.48*</b>	<b>0.77</b>
MA(3,9)	<b>0.31</b>	<b>0.58</b>	<b>0.80</b>	<b>0.22</b>	<b>0.43</b>	<b>0.51</b>
MA(1,12)	<b>0.52*</b>	<b>0.79*</b>	<b>0.92**</b>	<b>0.46*</b>	<b>0.65*</b>	<b>0.81*</b>
MA(2,12)	<b>0.39*</b>	-0.32	<b>0.05</b>	<b>0.28*</b>	-0.27	<b>0.03</b>
MA(3,12)	-0.11	<b>0.05</b>	<b>0.07</b>	-0.16	-0.02	<b>0.29</b>
MOM(9)	<b>0.29</b>	<b>0.43</b>	<b>0.91</b>	0.00	<b>0.25</b>	<b>0.52</b>
MOM(12)	<b>0.27</b>	<b>0.44</b>	<b>0.93</b>	0.00	<b>0.27</b>	<b>0.58</b>
VOL(1,9)	<b>0.52*</b>	<b>0.67*</b>	<b>0.56</b>	<b>0.11</b>	<b>0.54</b>	<b>0.53</b>
VOL(2,9)	<b>0.54*</b>	<b>0.73*</b>	<b>0.88</b>	<b>0.44*</b>	<b>0.65</b>	<b>0.85</b>
VOL(3,9)	<b>0.30</b>	<b>0.70*</b>	<b>0.88*</b>	-0.06	<b>0.60*</b>	<b>0.83*</b>
VOL(1,12)	<b>0.16</b>	<b>0.78*</b>	<b>0.89*</b>	-0.18	<b>0.61*</b>	<b>0.82</b>
VOL(2,12)	<b>0.16</b>	<b>0.50</b>	<b>0.79</b>	-0.04	<b>0.25</b>	<b>0.58*</b>
VOL(3,12)	<b>0.60*</b>	<b>0.69</b>	<b>0.71*</b>	<b>0.46*</b>	<b>0.57*</b>	<b>0.80*</b>
DMMA	<b>0.60*</b>	<b>0.80*</b>	<b>1.01**</b>	<b>0.49*</b>	<b>0.67*</b>	<b>0.85*</b>

Notes : Out-of-sample  $R^2$  ( $R^2_{OS}(\%)$ ) of single-predictor models including or excluding time-varying coefficients. The description of predictors is as follows: dp is the dividend-price ratio; dy is the dividend yield; ep is the earnings-price ratio; de is the dividend-payout ratio; svar is the stock variance; bm is the book-to-market ratio; ntis is the net equity expansion; tbl is the treasury bill rate; lty is the long-term yield; ltr is the long-term return; tms is the term spread; dfy is the default yield spread; dfr is the default return spread and infl is the inflation. MA( $s,l$ ), MOM( $l$ ), VOL( $s,l$ ) are technical indicators, based on moving average, momentum and volume strategy respectively ( $s=1,2,3$  and  $l=9,12$ ). See more details about the statistical evaluation in Table 2.3.

TABLE 2.6: Economic Evaluation

Panel A: Dynamic Mixture Model Averaging (DMMA)						
	Period:1960+		Period:1976+		Period:1988+	
	<i>CER</i>	<i>SR</i>	<i>CER</i>	<i>SR</i>	<i>CER</i>	<i>SR</i>
DMMA	<b>5.15</b>	<b>0.08</b>	<b>6.24</b>	<b>0.10</b>	<b>7.41</b>	<b>0.15</b>
Panel B: Equal Weights (EW)						
EW ( $\alpha=0$ )	<b>5.44</b>	<b>0.09</b>	<b>6.34</b>	<b>0.11</b>	<b>7.26</b>	<b>0.14</b>
EW-CC ( $\lambda=1, \alpha=0$ )	<b>4.15</b>	0.07	<b>5.54</b>	<b>0.10</b>	<b>7.09</b>	<b>0.14</b>
Panel C: Bayesian Model Averaging (BMA)						
BMA ( $\alpha=1$ )	<b>5.04</b>	0.07	<b>5.56</b>	<b>0.09</b>	<b>6.30</b>	<b>0.13</b>
BMA-CC ( $\lambda=1, \alpha=1$ )	2.49	0.03	<b>4.13</b>	0.07	<b>5.74</b>	0.12
Panel D: Dynamic Model Averaging (DMA)						
$\lambda=0.90, \alpha=0.90$	3.27	0.04	<b>4.90</b>	0.08	<b>7.04</b>	<b>0.14</b>
$\lambda=0.95, \alpha=0.90$	3.39	0.04	<b>4.48</b>	0.07	<b>6.62</b>	<b>0.13</b>
$\lambda=0.99, \alpha=0.90$	3.23	0.04	<b>4.53</b>	0.07	<b>6.52</b>	<b>0.13</b>
$\lambda=0.90, \alpha=0.95$	<b>4.12</b>	0.05	<b>5.05</b>	0.08	<b>7.01</b>	<b>0.14</b>
$\lambda=0.95, \alpha=0.95$	<b>4.23</b>	0.06	<b>5.55</b>	<b>0.09</b>	<b>7.53</b>	<b>0.15</b>
$\lambda=0.99, \alpha=0.95$	<b>4.89</b>	0.07	<b>5.85</b>	<b>0.09</b>	<b>7.56</b>	<b>0.15</b>
$\lambda=0.90, \alpha=0.99$	<b>4.90</b>	0.07	<b>4.97</b>	0.08	<b>6.00</b>	0.12
$\lambda=0.95, \alpha=0.99$	<b>4.72</b>	0.07	<b>4.81</b>	0.08	<b>6.05</b>	0.12
$\lambda=0.99, \alpha=0.99$	<b>4.92</b>	0.07	<b>6.22</b>	<b>0.10</b>	<b>6.50</b>	<b>0.13</b>
HM	3.39	0.07	3.93	0.08	5.25	0.12

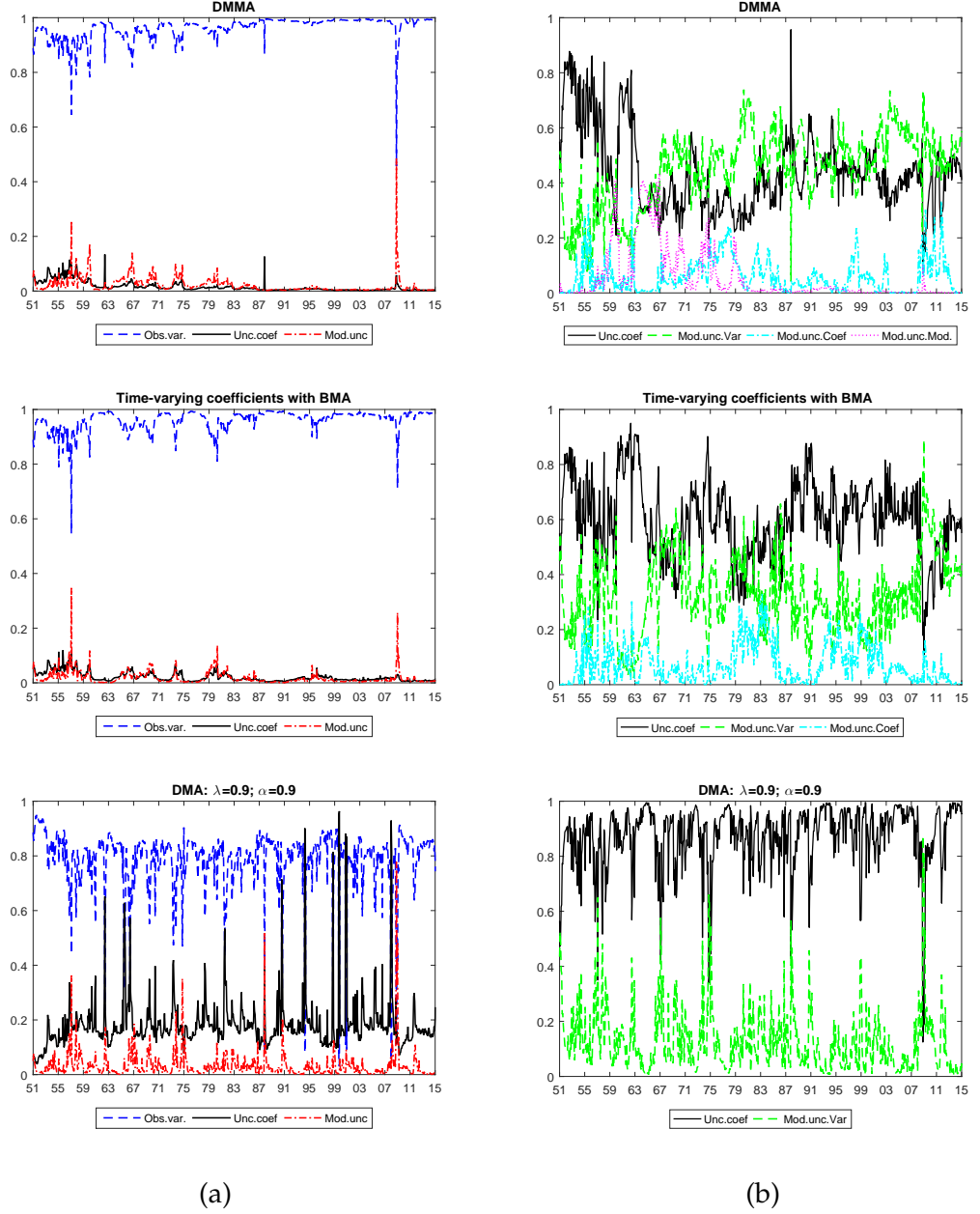
*Notes:* Economic predictability for different predictive models using the certainty equivalent return (*CER*) and monthly Sharpe Ratio (*SR*) compared with a historical mean model (HM) for a mean-variance investor who allocates wealth between equities and risk-free assets using different forecasts from different models. We consider different model combination methods, including combination with equal weights (EW) in Panel B, Bayesian model averaging (BMA) in Panel C and also all the possible dynamic model averaging (DMA) models in Panel D. The risk aversion coefficient for a mean-variance investor is 3 and we assume a 50 basis points percentage transactions cost per transaction when calculating *CER*. Bold font suggests that the statistics of that predictive model is larger than the corresponding one of HM. Following Dangl and Halling (2012), we study three different evaluation periods: 1960+, 1976+ and 1988+.

TABLE 2.7: Business Cycle Analysis

Panel A: Dynamic Mixture Model Averaging (DMMA)				
DMMA	$R_{OS}^2(\%)$		$\Delta CER$	
	Recession	Expansion	Recession	Expansion
	<b>5.19</b>	<b>0.23</b>	<b>19.01</b>	<b>0.22</b>
Panel B: Equal Weights (EW)				
EW ( $\alpha=0$ )	<b>4.22</b>	<b>0.25</b>	<b>17.90</b>	<b>0.18</b>
EW-CC ( $\lambda=1, \alpha=0$ )	<b>1.93</b>	<b>0.48</b>	<b>5.18</b>	<b>0.63</b>
Panel C: Bayesian Model Averaging (BMA)				
BMA ( $\alpha=1$ )	<b>2.60</b>	-2.92	<b>20.65</b>	-1.31
BMA-CC ( $\lambda=1, \alpha=1$ )	<b>2.83</b>	-2.66	<b>17.90</b>	-1.90
Panel D: Dynamic Model Averaging (DMA)				
$\lambda=0.90, \alpha=0.90$	-10.70	-9.80	<b>18.14</b>	-2.78
$\lambda=0.95, \alpha=0.90$	-11.56	-10.19	<b>18.56</b>	-2.88
$\lambda=0.99, \alpha=0.90$	-12.40	-11.42	<b>19.66</b>	-2.62
$\lambda=0.90, \alpha=0.95$	-7.74	-5.52	<b>22.80</b>	-2.87
$\lambda=0.95, \alpha=0.95$	-8.40	-5.71	<b>21.25</b>	-2.78
$\lambda=0.99, \alpha=0.95$	-6.70	-6.15	<b>23.00</b>	-2.39
$\lambda=0.90, \alpha=0.99$	<b>2.11</b>	-1.46	<b>12.04</b>	-1.87
$\lambda=0.95, \alpha=0.99$	<b>1.79</b>	-1.53	<b>12.32</b>	-1.63
$\lambda=0.99, \alpha=0.99$	<b>2.44</b>	-1.81	<b>17.37</b>	-1.23

Notes: Business cycle analysis using out-of-sample  $R^2$  ( $R_{OS}^2(\%)$ ) and certainty equivalent return gain ( $\Delta CER$ ) compared with historical mean (HM). Bold font suggests that the statistics of that predictive model is larger than the corresponding one of HM. The sample period is from November 1961 to December 2015.

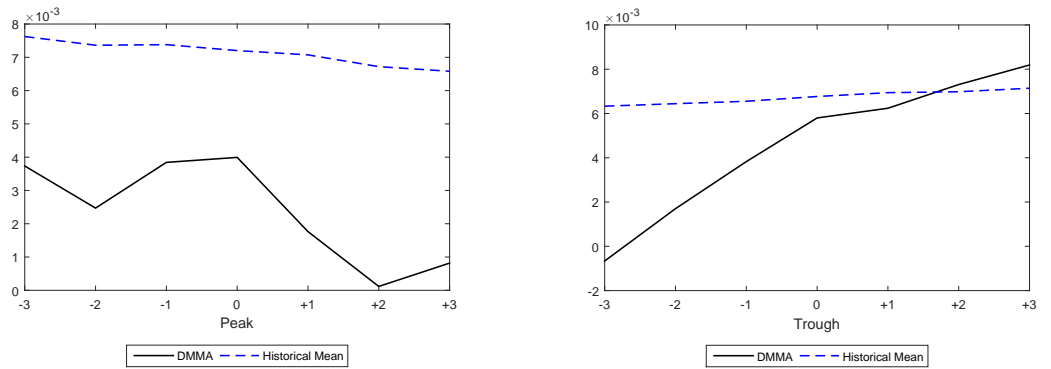
FIGURE 2.1: Sources of Prediction Variance for Dynamic Mixture Model Averaging (DMMA), Bayesian Model Averaging (BMA) and Dynamic Model Averaging (DMA)



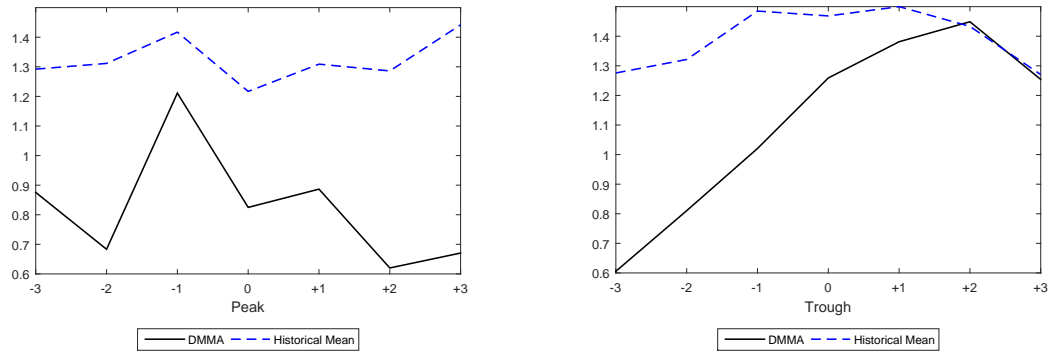
Notes: Decomposition of the prediction variance for DMMA, possible degrees of time variation in coefficients with BMA and DMA (take  $\lambda = 0.9, \alpha = 0.9$  as an example). Column (a) of the Figure plots the relative weights of observational variance (Obs.var.), expected variance from errors in the estimation of coefficients (Unc.coef.) and variance caused by the model uncertainty (Mod.unc.). Column (b) excludes observational variance and investigates expected variance from errors in the estimation of coefficients (Unc.coef.), variance caused by the uncertainty regarding the variable selection (Mod.unc.Var), variance caused by the uncertainty regarding different degrees of time variation in coefficients (Mod.unc.Coef) and in forecasting models (Mod.unc.Mod). Particularly, in Panel B, for time-varying coefficients with BMA, Mod.unc.Mod is neglected as  $\alpha = 1$ . Similarly, for DMA, Mod.unc.Mod and Mod.unc.Coef are excluded as  $\lambda$  and  $\alpha$  are invariant.

FIGURE 2.2: Equity Premium Forecasts and Portfolio Weights  
Around Peaks and Troughs

Panel A: Equity Premium Forecasts

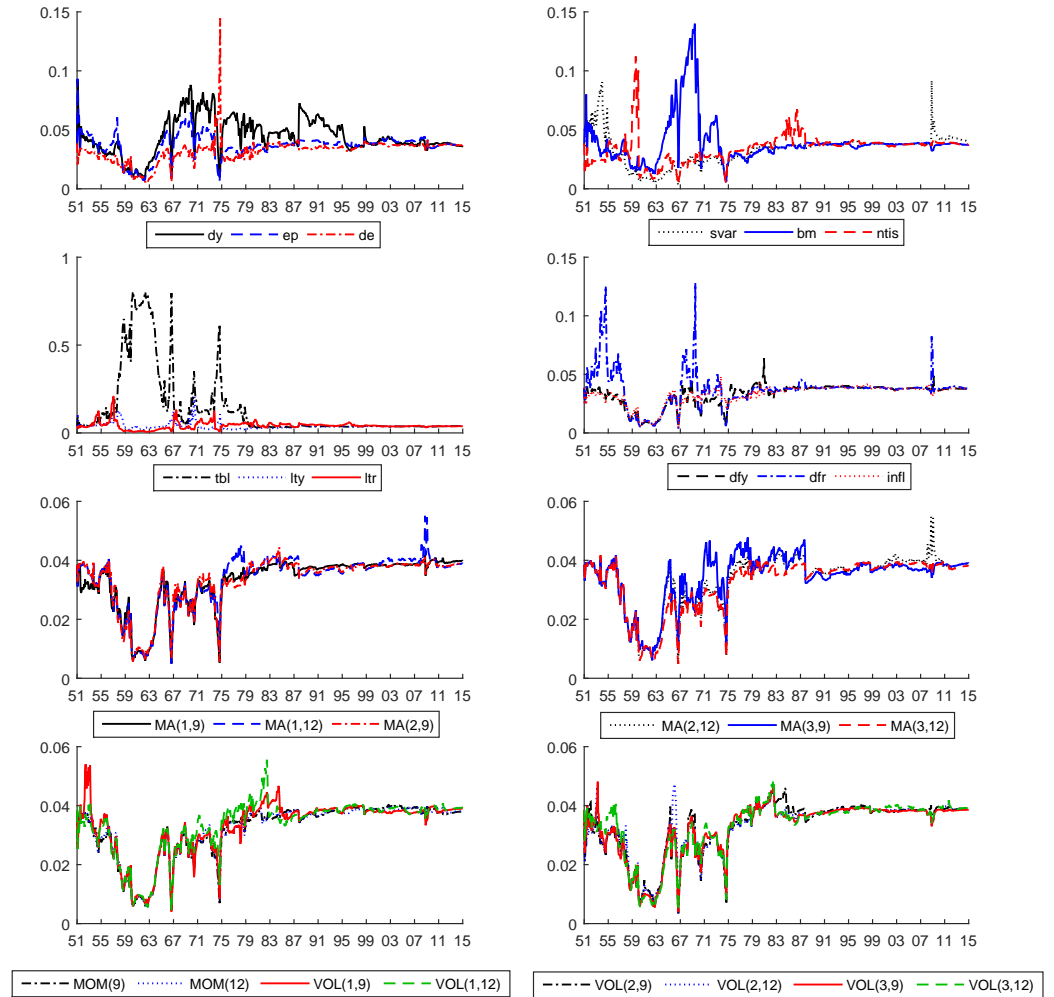


Panel B: Portfolio Weights



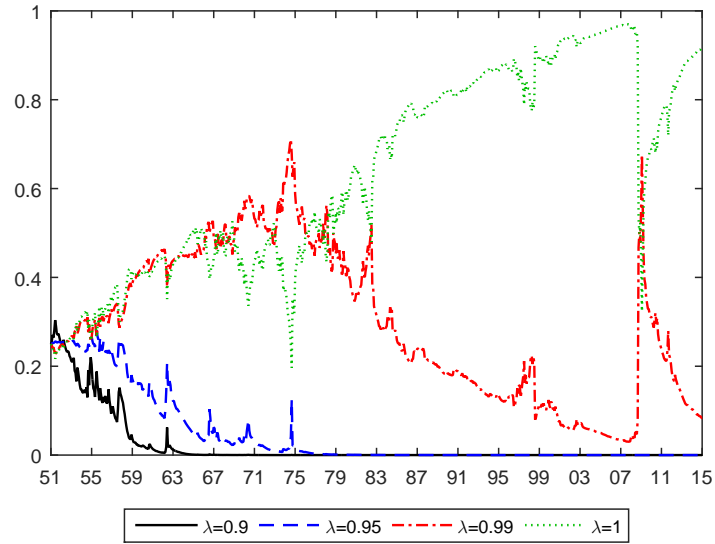
*Notes:* Equity premium forecasts and the portfolio weights attached to risky assets around peaks and troughs. Panel A demonstrate the predicted equity premium using DMMA and historical mean. Panel B presents the portfolio weights of the risky asset for a mean-variance investor, using predictions from DMMA and historical mean. As mentioned in Section 2.4.1.2, we limit the percentage invested in equities to be between 0% and 150%.

FIGURE 2.3: Time-Varying Inclusion Probabilities for Different Predictors



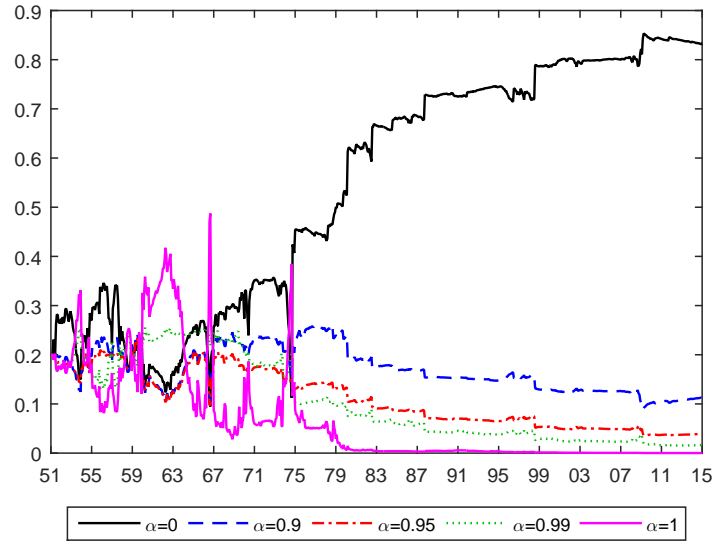
*Notes:* Time-varying inclusion probabilities for different predictors in the DMMA model. The description of predictors is as follows: dp is the dividend-price ratio; dy is the dividend yield; ep is the earnings-price ratio; de is the dividend-payout ratio; svar is the stock variance; bm is the book-to-market ratio; ntis is the net equity expansion; tbl is the treasury bill rate; lty is the long-term yield; ltr is the long-term return; tms is the term spread; dfy is the default yield spread; dfr is the default return spread and infl is the inflation.  $MA(s,l)$ ,  $MOM(l)$ ,  $VOL(s,l)$  are technical indicators, based on moving average, momentum and volume strategy respectively ( $s=1,2,3$  and  $l=9,12$ ).

FIGURE 2.4: Posterior Probabilities of Degrees of Time Variation in Coefficients ( $\lambda$ )



*Notes:* Posterior probabilities of models with a specific degree of time variation of coefficients ( $\lambda$ ) for DMMA. Particularly,  $\lambda \in [0.90, 0.95, 0.99, 1]$ .

FIGURE 2.5: Posterior Probabilities of Degrees of Time Variation in Forecasting Models ( $\alpha$ )



*Notes:* Posterior probabilities of models with a specific degree of time variation of forecasting models ( $\alpha$ ) for DMMA. Particularly,  $\alpha \in [0, 0.90, 0.95, 0.99, 1]$ .



## **Chapter 3**

# **Global Financial Integration In a Changing World**

### **3.1 Introduction**

Global financial integration has been an important area of study for both academic researchers and policy makers. The surge of cross-border financial flows has led to greater investment and growth opportunities, more efficient capital allocation and consumption smoothing, and improved international risk-sharing possibilities (Carrieri et al. (2007), Pukthuanthong and Roll (2009), Eiling and Gerard (2014), and Suzuki (2014)). Consequently, financial integration is likely to generate short- and long-run welfare benefits (Colacito and Croce, 2010). On the other hand, financial integration also increases spillovers and contagion risk, in the sense that the international financial system is more vulnerable to global shocks or shocks that originate in one country (Kose et al. (2009), Berger and Pozzi (2013), and Castiglionesi et al. (2017)). Moreover, increasing financial integration tends to affect countries' policy targets and undermine domestic policies' effectiveness (Blanchard et al. (2010) and Billio et al. (2017)). It is therefore essential to accurately measure financial integration and to identify the fundamentals that drive integration.

A natural way to measure financial integration is through a dynamic factor model, in which the expected stock return is driven by the estimated world market return (global factors) extracted from stock markets.<sup>1</sup> This method is in line with asset pricing theory, particularly with the International CAPM (ICAPM), and the global financial cycle, proposed by Rey (2015).<sup>2</sup> Integration is therefore calculated as the fraction of a country's stock return explained by the global factors.<sup>3</sup> If the fraction explained by global factors is small, with local effects more crucial than global effects, the country tends to be segmented from financial globalization. Whereas if the expected returns of the country can largely be explained by the global factors, a high degree of financial integration is evident. However, a common assumption in the previous literature of using ICAPM to measure integration is that both the process driving volatility and the linkage between global factors and individual stock return do not vary over time. Nonetheless, this assumption of structural stability seems to be implausible, especially when the exposures to global factors and local factors are time-varying due to regulatory and economic changes.<sup>4</sup> For example, Bekaert et al. (2009) establish risk-based factor models to study international

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<sup>1</sup>A large number of the research on financial integration has focused on stock markets (Bekaert et al. (2009), Pukthuanthong and Roll (2009), Eiling and Gerard (2014), and Everaert and Pozzi (2016)). We adopt a *de facto* measure of financial integration which explores observable phenomena resulting from changeable stock markets, instead of the *de jure* measure that heavily relies on the analysis of capital account openness and legal restrictions, see Chinn and Ito (2008) and Abiad et al. (2010) for details. This is partly because the process of financial integration can be gradual and even though regulatory changes can be officially dated, the effect of these policies frequently come with a delay. The *de facto* measure, therefore, shall encompass *de jure* changes.

<sup>2</sup>For ICAPM, see among others, Harvey (1991) and Bekaert and Harvey (1995) for more details. For the global financial cycle, see Fratzscher (2012), Cerutti et al. (2015) and Byrne and Fiess (2016).

<sup>3</sup>See Bekaert and Harvey (1995), Carrieri et al. (2007), Bekaert et al. (2009), Berger and Pozzi (2013) and Eiling and Gerard (2014) for details.

<sup>4</sup>The importance of time-varying coefficients and stochastic volatility has also been emphasized in the macroeconomic literature. Using a large U.S. macroeconomic dataset, Stock and Watson (2009) find significant instability in factor exposures around 1984. Del Negro and Otrok (2008) develop a dynamic factor model with time-varying factor loadings and stochastic volatility to measure changes in international business cycles.

stock return comovement and underline the importance of time-varying factor loadings using rolling window estimates. Berger and Pozzi (2013) also apply ICAPM to measure stock market integration, where country-specific and global risk premiums, and their variances, are estimated from a latent factor decomposition through the use of state space methods that allow for GARCH errors. The recent paper of Bekaert and Mehli (2017) suggests that factor exposures may vary with global shocks and shifts in global risk aversion over time. Many of the papers in this literature illustrate that the ICAPM with constant factor loadings and volatility may be too restricted to successfully model and predict financial integration, especially when the global stock markets are volatile.

In this paper, therefore, we employ an ICAPM framework that allows us to capture short run transitory and long run structural changes in the economy that might affect the measurement of financial integration.<sup>5</sup> To construct the financial integration measure, we begin by using principal components to capture the comovement of the international stock markets for 18 advanced economies over the period 1970-2017. Stock returns then can be explained by a country-specific risk factor and global factors, which are characterized by time-varying factor loadings and stochastic volatility. Our method does not depend upon rolling window or recursive estimates, but explicitly models time-variation in the coefficients and volatility from the data.

Our contribution goes further than developing a measure of financial integration. We investigate the characteristics of cross-country financial integration and assess the general perception that it has increased substantially during the past decades. The flexibility of our method also allows us to analyze

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<sup>5</sup>Another strand of the literature has relied on cross-country correlations between different stock markets as a measure of integration. However, as argued by Pukthuanthong and Roll (2009), even perfectly integrated stock markets can be weakly correlated and Forbes and Rigobon (2002) suggest that integration drawn from correlations could be biased upward due to conditional heteroskedasticity.

which economic elements drive cross-country integration. In particular, we decompose the total return variance into global, local and estimation risk and aim to understand the way in which these three components influence integration. Moreover, this work forecasts financial integration using macroeconomic fundamentals including the CBOE volatility index (VIX), which is closely related to the global financial cycle (see Miranda-Agrippino and Rey (2015), Rey (2015), and Byrne and Fiess (2016)). To the best of our knowledge, this is the first work that systematically studies financial integration predictability across countries and the importance of its determinants over time. This out-of-sample predictability has important implications for risk management, portfolio allocation of the international stock markets, as well as the effectiveness of domestic policies.

Among papers studying the importance of instabilities of factor loadings and volatility of ICAPM to measure integration, we note contributions by Pozzi and Wolswijk (2012), Berger and Pozzi (2013) and Everaert and Pozzi (2016). However, while they discuss time-variation in the parameters of ICAPM model and its ability to capture changes in integration, they do not explicitly examine the effect of the former upon the latter. Therefore, our study complements theirs, by testing time-varying betas *ex ante* using the Elliott and Müller (2006) test, and by comparing the difference between constant and time-varying parameter ICAPM with stochastic volatility. As far as we know, our chapter is the first work to test time-variation in factor loadings when constructing financial integration. We also extend the analysis in the above papers to examine the origins of changes in integration from the perspective of decomposition and time series prediction.

To preview our results, we uncover that although financial integration displays a secular upward trend, none of the advanced economies we consider consistently achieve full stock market integration. Importantly, integration

typically reaches local maxima during the global financial crisis in 2008. But there exists some country and region specific effects: such as the increasing integration for Hong Kong and Singapore due to the Asia Crisis of 1997 and increased European integration during the European sovereign debt crisis. Essentially, time-variation in factor loadings and stochastic volatility are crucial to capture dynamics in financial integration. By applying trend and break tests, we confirm that financial integration has experienced a structural change and generally increased for our sample of advanced economies. We also find that principally, instead of a decreasing country-specific effect, increasing global risk is the key element that drives integration. Finally, we provide formal evidence that integration is highly predictable using macroeconomic and financial indicators. In general, the VIX index is the main determinant of financial integration, followed by cross-country trade openness.

The remainder of this chapter is set out as follows. Section 3.2 lays out the model framework to measure financial integration. Section 3.3 discusses the data and Section 3.4 studies the characteristics of our measure of financial integration. Section 3.5 presents the trend and break tests results. Section 3.6 analyzes the economic mechanisms that drive integration and Section 3.7 concludes.

## **3.2 Model Framework**

Financial integration can be constructed from a dynamic factor model that satisfies the following principles: i) The model should be flexible enough to account for changes in the global factors and country-specific effects; ii) The model should accommodate the volatility of financial markets; iii) The model

should be data-driven and the integration measure should be implicitly derived from the estimation process. Therefore, our starting point is a time-varying factor loadings and volatility model which captures the relationship between global factors and country-specific stock returns under a Bayesian state space framework. Financial integration is measured therefore as the evolving proportion of variance explained by the global factors.

### 3.2.1 A Dynamic Model with Stochastic Volatility

Consider an International CAPM model with  $r_{i,t}$  as the excess return for country  $i$  at period  $t$ :

$$r_{i,t} = \mu_{i,t} + \beta_{i,t}^p r_t^p + \varepsilon_t \sqrt{\exp(\ln h_{i,t})} \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad \varepsilon_t \sim N(0, 1) \quad (3.1)$$

where  $\mu_{i,t}$  is the unobserved country-specific factor,  $r_t^p$  are the principal components we obtained which can be treated as the excess return of the world equity portfolio. The superscript  $p$  in  $r_t^p$  refers to the number of principal components in our model and  $\varepsilon_t$  denotes normally distributed errors with mean zero and variance one. An important feature of our methodology is that factor exposures on different global factors for each country  $\beta_{i,t}^p$  and the idiosyncratic variance  $h_{i,t}$  are time-varying.

Denote the time-varying parameter set  $B_{i,t} = \{\mu_{i,t}, \beta_{i,t}^p\}$ , then for different countries, time-varying coefficients in Equation (3.1) follow a random walk process:

$$B_{i,t} = B_{i,t-1} + e_{i,t} \quad e_{i,t} \sim N(0, Q_i) \quad (3.2)$$

where  $e_{i,t}$  is the error term with mean zero and time-varying variance  $Q_i$ .

Bekaert et al. (2009) argue that flexibility in the modeling of betas is important in capturing underlying structural changes in financial markets. Occasionally, the financial integration literature focuses upon the factor loadings on the global factor (i.e., the betas in our model) as the measure of stock market integration.<sup>6</sup> However, this measure can be problematic, as a fully integrated country which only depends on global factors can also have low loading betas.

We argue that stochastic volatility is also essential to the construction of our measure of financial integration. Here, we assume that the shock to stochastic volatility  $h_{i,t}$  in Equation (3.1) is independent of  $r_t^p$ , which is in line with the theoretical literature. The GARCH type models applied in Carrieri et al. (2007) and Berger and Pozzi (2013) do not share this distinctive characteristic. Specifically, the variance of the error term  $h_{i,t}$  in Equation (3.1) evolves as:

$$\ln h_{i,t} = \ln h_{i,t-1} + v_{i,t} \quad v_{i,t} \sim N(0, g_i) \quad (3.3)$$

where  $v_{i,t}$  is the disturbance term with mean zero and time-varying variance  $g_i$ .

This time-varying factor loadings with stochastic volatility model can be estimated by combining the Carter and Kohn algorithm with the Metropolis algorithm in a Bayesian setting (Blake and Mumtaz, 2012). We set an inverse Wishart prior for  $B_i$ , where  $Q_{i,0} = k \times Q_{i,ols} \times T_0$ .  $T_0$  is the length of training sample and we set  $T_0 = 52$ , equivalent to the number of weeks in one year. For country  $i$ ,  $Q_{i,ols}$  is the OLS estimation of the variance covariance matrix for  $B_i$  using the training sample period and  $k$  is a small scaling factor. An inverse Gamma prior is set for  $g$  such as  $p(g_i) \sim IG(q_0, v_0)$ , where the prior scale  $q_0=0.01$  and the prior degree of freedom  $v_0=1$ .

Details on implementation of time-varying coefficients with stochastic volatility model are provided in the online appendix. To estimate the model, 50,000

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<sup>6</sup>For instance, Baele et al. (2004), Schotman and Zalewska (2006), Kizys and Pierdzioch (2009) and Bekaert and Mehli (2017) take the betas as the integration.

draws are made based on the algorithm above, with the first 45,000 as burn-in draws and the last 5,000 draws used to construct financial integration.

### 3.2.2 Measuring Financial Integration

In this chapter, we adapt an ICAPM approach to measure financial integration. Empirical integration measures such as simple correlations can be contaminated because of volatility bias (see e.g., Forbes and Rigobon (2002) and Dumas et al. (2003)). Correlations may increase, in particular, due to increasing common factor variance, rather than increasing factor exposures. Eiling and Gerard (2007) and Pukthuanthong and Roll (2009) measure integration by focusing on the proportion of total variance explained by the global factors for the stock market returns and suggest this is a better way to measure financial integration than simple correlations.<sup>7</sup> Therefore, we generally adapt this method to measure integration. A time-varying stock market integration  $TVI_{i,t}$  for country  $i$  at time period  $t$  is denoted as:

$$TVI_{i,t} = \frac{V_t(\beta_{i,t}^p r_t^p)}{V_t(r_{i,t})} = \frac{V_t(\beta_{i,t}^p r_t^p)}{V_t(\mu_{i,t} + \beta_{i,t}^p r_t^p + \varepsilon_t \sqrt{\exp(\ln h_{i,t})})} = \frac{V_t(\beta_{i,t}^p r_t^p)}{V_t(\mu_{i,t} + \beta_{i,t}^p r_t^p) + h_{i,t}} \quad (3.4)$$

where  $V_t$  denotes the variance of corresponding terms, based upon Equation (3.1).<sup>8</sup>

The integration measure in Equation (3.4) lies within zero and one. In extreme, if a country is fully detached from the world, local or regional factors

<sup>7</sup>Even though Pukthuanthong and Roll (2009) claim that the integration measure they apply based on the proportion of a countrys returns that can be explained by global factors, the multi-factor  $R$ -square indicator they actually use cannot distinguish whether the explanatory power is truly global or country-specific.

<sup>8</sup>As acknowledged by Pukthuanthong and Roll (2009), when sampling error is admitted, there will be some inevitable variation in the estimated integration measure in Equation (3.4) even though the true integration is constant. They suggest this is not likely to be a serious problem as factor variation and estimation error are common. We further adjust this bias by relying on longer-term trends using quarterly instead of weekly data and investigate the importance of allowing stochastic volatility in Section 3.4.3.



dominate the market while factor exposure  $\beta_{i,t}^p$  tends to be zero, and its integration will be negligible. On the contrary, a more integrated country is highly susceptible to the global factors and has an integration index close to one. Our integration measure echos the statement by Bekaert and Harvey (1995): a market is completely integrated if the common world factors can explain its expected returns, whereas segmentation will prevail if these common factors have little power to explain the expected returns.

We argue that the total variance of stock returns can be decomposed into three parts: variance of the global factor, variance of the country effect and stochastic volatility from Equation (3.1). Therefore,  $TVI_{i,t}$  will increase when the risk of global factor  $\beta_{i,t}^p r_t^p$  increases, when the risk of the local effect  $\mu_{i,t}$  decreases, and/or when the stochastic volatility  $h_{i,t}$  decreases. We study the sources of uncertainty of stock returns in Section 3.6.1 and investigate which components drive the financial integration dynamics.

Compared to other integration measures derived from the ICAPM model, a key innovation of our study is that we accommodate time-varying local effect  $\mu_{i,t}$ , factor loadings  $\beta_{i,t}^p$  and stochastic volatility  $h_{i,t}$  in the construction of the financial integration. Whereas, for a model with constant coefficients and volatility, the dynamics in the integration measure will only be driven by time-variation in the global factors  $r_t^p$  extracted from individual stock markets, according to Equation (3.4). This may be unreasonable, especially in a changing world, with changes in economic conditions, *de jure* financial openness and global risk. We further assess ex ante the necessity of time-varying factor loadings using a statistical test and compare our model with the constant loadings and variance model in Section 3.4.3.

### 3.3 Data

We focus on the excess stock returns using the MSCI index for 18 advanced economies around the world: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States. These countries have considerable influences on the world financial market and are included in the MSCI developed country index. Moreover, they have the longest data availability on Datastream. Similar to Bekaert et al. (2009), weekly returns data is used to alleviate the problems caused by nonsynchronous trading days and opening hours for different countries at higher frequencies. In total, 2544 weekly observations are obtained over the period 1970:01-2017:01. We present the country-specific MSCI price index and its Datastream mnemonic in the appendix.

The excess stock returns is measured using continuously compounded returns net of the U.S. risk-free rate:

$$r_{i,t} = (\log(\frac{P_{i,t}}{P_{i,t-1}})) * 100 - r_{ft} \quad (3.5)$$

where  $P_{i,t}$  is the price index for country  $i$  at time  $t$  and  $r_{ft}$  is the U.S. weekly risk-free rate at time  $t$ . We use the MSCI price index in US dollars, to take the perspective of an international investor.<sup>9</sup> This allows us to take possible reasons, such as exchange rate risk, for comovement variability into account. Regarding  $r_{ft}$ , we use the weekly three-month U.S. T-Bill rate provided by the Federal Reserve Bank of St. Louis in annualized percentage terms. To convert this annual risk-free rate to a weekly rate, we divide the annualized three-month T-Bill by 52.

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<sup>9</sup>The MSCI price index does not include dividends. It would be preferable to use total return index which includes reinvested dividends. However, total return index has shorter data availability. We therefore use the MSCI price index to investigate longer horizon of international stock returns.

## 3.4 Financial Integration

In this section, we first report the global factors obtained by out-of-sample principal component analysis. Then we demonstrate the cross-country financial integration and analyze its distinctive features.

### 3.4.1 Out-of-Sample Principal Components and Co-movement

Principal component analysis (PCA) is widely used in the literature and is advantageous in determining the co-movement in different areas as only a few components are needed to summarize the observed variation in the data. For instance, Pukthuanthong and Roll (2009) investigate the evolution of market integration based on the explanatory power of a multi-factor model. Financial integration is then calculated as the adjusted R-square from the regressions of stock market returns on the estimated factors. However, it is not well defined whether the estimated factors are truly global or country-specific. Volosovych (2011) also implements PCA to construct an integration index. He uses the percentage of variance explained by the first principal component as the measure of financial integration in the bond market. Nonetheless, this measure simply generates an identical integration index for all the countries and using a single global factor might not be enough to reveal the important information about integration.

Following Pukthuanthong and Roll (2009), we conduct an out-of-sample principal component analysis to capture global factors in the stock market across countries, where principal components are estimated using the eigenvectors obtained from the previous calendar year. In other words, we first conduct the common PCA for the year 1970. Then the eigenvectors from 1970 will

be used on the integration series from 1971. This is repeated in each calendar year until the final available full sample year 2016.<sup>10</sup>

To identify the number of common factors, we use the information criteria (IC) proposed by Bai and Ng (2002), which is suggested to have better power and size properties than the usual AIC and BIC measures.<sup>11</sup> The IC3 criteria selects two principal components. Bai and Ng (2002) indicate that this criteria is more reliable especially in the presence of cross sectional correlation, which is likely in our case.

We calculate the average cumulative proportion of variance explained by the out-of-sample principal components.<sup>12</sup> Among the 18 principal components, the first component explains over 80% of the variance and the first two components explain over 90% of the total variance. This clearly implies the existence of global factors and further confirms the number of common factors selected by the IC3 criteria. The fact that the first component explains over 80% of the variance also reflects the finding of global financial cycle of Miranda-Agrippino and Rey (2015). They suggest that one global factor explains a large part of the variance of returns of risky assets around the world and interpret this global factor as reflecting realized world market volatility of risky assets and the market-wide risk aversion.

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<sup>10</sup>As we implement the out-of-sample PCA, the resulting principal components are not exactly orthogonal. Nevertheless, the correlations between out-of-sample principal components are small and Pukthuanthong and Roll (2009) suggest that it would not be a problem using these components as explanatory variables in regressions.

<sup>11</sup>As acknowledged by Bai and Ng (2002), IC3 criteria is a function of both  $N$  and  $T$  (the cross-section dimension and the time dimension, respectively) and it can lead to a consistent estimate of numbers of factors. Whereas, the usual AIC and BIC, which are functions of  $N$  or  $T$  alone, do not work well specially when  $N$  and  $T$  are large.

<sup>12</sup>We present the figure of percentage variance explained by principal components in the online appendix.

### 3.4.2 Financial Integration

As acknowledged by Pukthuanthong and Roll (2009), to mitigate the problem that the integration measure will be biased upward when global factor volatility happens to be greater than the total country volatility, it is prudent to use longer-term trends instead of shorter-term variation in the estimated financial integration. We, therefore, use the weekly MSCI return data to estimate quarterly financial integration from 1971Q1 to 2017Q1, to alleviate short-run disturbances.<sup>13</sup>

Table 3.1 shows the summary statistics of the estimated integration for our countries of interest, indicating that integration reveals a substantial amount of heterogeneity. Over the whole sample period, Hong Kong has the largest integration index among the 18 advanced economies. Due to almost free port trade, well established and regulated financial market as well as close ties with mainland China, Hong Kong has the highest degree of economic and financial freedom since 1995 (Heritage, 2017). On the other hand, Japan has the lowest integration compared to others, only with large fluctuations recently. This is in line with earlier findings that the integration of Japan has not increased substantially over time (Berben and Jansen (2005) and Berger and Pozzi (2013)). The United States, as the largest economy in the world, also shows greater integration compared with other countries. In general, the financial integration exhibits serial correlation and we find that for most of the countries the null hypothesis of a unit root cannot be rejected, see  $p_{ADF}$  in Table 3.1.

We demonstrate the financial integration for 18 advanced economies in Figure 3.1. Due to the reversals in the integration series, we also superimpose a

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<sup>13</sup>We first obtain weekly financial integration then convert it to quarterly data by taking means. This transformation is convenient for us to conduct the prediction in Section 3.6.2 as all the macroeconomic fundamentals are quarterly data. Financial integration starts from 1971Q1 instead of 1970Q1 since we use the first year sample as the training period.

plot of the Hodrick-Prescott (H-P) filtered trend series to focus upon the long-term trend.<sup>14</sup> Despite the variability, almost all the countries appear to display an upward time trend. This is consistent with the fact that capital mobility and cross-border financial flows have generally increased from the mid-1980s, and financial liberalization policies can stall and even reverse, causing fluctuations in integration. We further check this argument in Section 3.5 by applying trend and break tests.

We also find that none of the advanced economies we consider achieve and maintain complete integration, confirming the statement that there still exists some market segmentation and benefits from international diversification. This is not surprising, as even with fully liberalized financial markets, due to the home bias puzzle, individuals and institutions still prefer investing at home rather than abroad. In contrast, according to the popular financial openness measure suggested by Chinn and Ito (2008) and the financial reform index proposed by Abiad et al. (2010), financial markets are entirely open for most of our economies of interest.

As expected, integration of almost all the countries reached their local maxima around 2008, at the peak of the financial crisis. Globally, the surge of cross-border financial flows in the decade before the crisis leads to the excessive growth in credit markets (Lane, 2013). The United States is generally considered to be the epicenter of the financial crisis due to speculative bubbles and crashes, and then it quickly spread to other countries around the world. This reflects the fact that high level of financial integration during time of stress could cause the international financial markets vulnerable. Additionally, the local maxima of integration around 2008 echos the argument from Bekaert and Mehli (2017) that in times of heightened market volatility global betas tend to increase significantly.

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<sup>14</sup>By convention, we set the smoothing parameter of the H-P filter to 1600 for quarterly data.

Our financial integration measure also suggests that despite the liberalization of financial markets during recent decades, the country-specific feature is still an essential element in interpreting the time variation in expected returns. Hence none of the countries are completely integrated. In particular, Figure 3.1 sheds light on the importance of cross-country differences in the evolution of financial integration. Examples include increases in integration for Hong Kong and Singapore due to the 1997 Asia financial crisis as well as the decreasing trend of integration for Japan during 1991 to 2007 as a result of the “lost decade” after the Japanese asset price bubble’s collapse. For European countries, integration rose rapidly as a result of the euro area debt crisis in 2010-2012, then it subsequently fell during the past four years due to implementation of new banking regulations and increasing sovereign risk. Moreover, the degree of financial integration was fairly high in some countries (e.g., Australia, Belgium, Canada, Hong Kong, Norway and the United States etc) around the 1973 oil crisis and the fall of the Bretton Woods system. We conclude that the evolution of financial integration over the last five decades has many similarities but also has substantial differences across countries. Our methods capture dynamics not only in the global factors but also in the country-specific financial markets.

### **3.4.3 Importance of Time-varying Factor Loadings and Stochastic Volatility**

So far we have presented the financial integration measure with time-varying betas and stochastic volatility. But do these conditional terms matter? In this section, we explicitly test why incorporating time-varying betas and stochastic volatility matter when deriving financial integration from our ICAPM model.

We first check whether there is persistent time variation in the factor loadings regardless of the data-generating process. Given a regression with individual stock return as the dependent variable and global factors as explanatory variables, we examine the stability of the regression model. Elliott and Müller (2006) propose an efficient test statistics that allows for many or a few breaks, clustered breaks, frequently occurring breaks, or smooth transitions to variation in the regression coefficients. Moreover, this test has good power and sample size even for models with heteroscedasticity. We therefore apply the Elliott and Müller (2006) test to examine whether we should incorporate time-varying betas *ex ante*. To the best of our knowledge, our study is the first one to systematically test the importance of time-variation in the betas of the ICAPM model.

Table 3.2 presents the results of the Elliott and Müller (2006) test. We strongly reject the null hypothesis that factor loadings of the ICAPM are constant over the whole period for every economy we investigate at the 1% significance level. This implies that there is statistical evidence of time-variation in factor loadings and we should take this feature into account. Otherwise, the inference using standard methods with restricted coefficients may be misleading.

To reinforce our point, after we identify time-variation in factor loadings, we investigate whether it matters when constructing our measure of financial integration. Therefore, we compare our integration measure with the one drawn from constant betas and risk. The simple ICAPM is measured using global factors as explanatory variables and stock return of each country as the dependent variable, with constant coefficients and volatility. Particularly, the variance-covariance matrix of the coefficients are heteroskedasticity robust. The integration is measured in the same way as described in Section 3.2.2.



Figure 3.2 shows the simple ICAPM integration measure with constant factor loadings and volatility. Counter-intuitively, there is little evidence of increased financial integration over time and excess sensitivity to outliers: after the initial data-points, financial integration peaks either during the financial crisis in 2008 or during the financial market crash in 1987.<sup>15</sup> Hence, the simple integration measure with constant factor and risk cannot reveal systematic differences cross countries. Importantly, the magnitude of the integration is negligible, with the largest integration being less than 0.05.<sup>16</sup> This negligible degree of integration is unable to explain the dynamics among different financial markets, especially with the development of trade linkages and financial liberalization over the recent decades.

As discussed in Section 3.2.2, dynamics in financial integration derived from a constant coefficients and volatility model is, by restriction, only driven by dynamics in the variance of global factors. Whereas, for our integration measure, time-varying coefficients and stochastic volatility also contribute to the changes in integration. Each national stock market locks onto the global factors in a time evolving and contrasting fashion. We therefore conclude that, integration is mainly driven by the time-variation presented in the factor loadings and the volatility derived simultaneously from Equation (3.1). This further proves that our financial integration is unlikely to be contaminated by the so-called heteroskedasticity or volatility bias (see e.g., Forbes and Rigobon (2002) and Pukthuanthong and Roll (2009)).

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<sup>15</sup>The integration derived from simple ICAPM starts from 1970 as there is no training data.

<sup>16</sup>Using a difference in means test, we confirm that integration measured using simple ICAPM is significantly smaller than that using our ICAPM with time-variation. The test statistics is reported in the appendix.

### 3.5 Trends and Breaks in Financial Integration

In the previous section, we presented evidence of a rising trend in financial integration, therefore, we are interested in whether this time trend is significant. Specifically, for each country, we focus on the regression:

$$TVI_t = a + b \cdot trend + u_t \quad (3.6)$$

where  $TVI_t$  is the financial integration identified in the previous section for each country,  $trend$  is a linear time trend, constant parameters are denoted by  $a$  and  $b$ , while  $u_t$  is the error term.

We apply the Perron and Yabu (2009a) test to examine the null hypothesis that  $H_0 : b = 0$ .<sup>17</sup> The advantage of this test is that it is still effective even without any prior knowledge of whether the series is trend-stationary or contains a unit root.<sup>18</sup> This is exactly our case as some countries are trend-stationary while others contain unit roots, as showed in Table 3.1. Perron and Yabu (2009a) show that by using the Feasible Quasi Generalized Least Squares, inferences on the slope coefficient can be measured using the simple standard Normal distribution with either  $I(0)$  or  $I(1)$  error components.

Table 3.3 reports the Perron and Yabu (2009a) test results for financial integration. According to the estimated trend coefficients, all of the countries increasingly integrate with each other during the past few decades. Not surprisingly, integration for Hong Kong increases by 3.49% per year and is the largest among all the countries, due to its status as a world financial center. Additionally, we strongly reject the null hypothesis that there is no time trend

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<sup>17</sup>Perron and Yabu (2009a) assume that  $u_t = a \cdot u(t-1) + A(L)(u(t-1) - u(t-2)) + e(t)$  where  $e(t) \sim i.i.d.(0, \sigma^2)$ .

<sup>18</sup>Bekaert et al. (2009) and Eiling and Gerard (2014) perform the Bunzel and Vogelsang (2005) trend test instead. However, Perron and Yabu (2009a) show that their procedure leads to better size and power properties than the tests proposed by Bunzel and Vogelsang (2005) and Harvey et al. (2007). This is because even though their tests are valid with either  $I(1)$  or  $I(0)$  errors, good properties of these random scaling tests disappear in finite samples. The Perron and Yabu (2009a) test is different from theirs and does not relate to random scaling.

at the 5% significance level for most of the countries we are interested in, except for Austria, Japan, Singapore and Switzerland. This suggests that integration has increased significantly for most of the economies we consider.

It is well known that tests for deterministic trends can be invalidated by shifts or structural breaks. To assess this probability, we apply the Perron and Yabu (2009b) test for breaks in the integration series. This approach is robust for stationary or integrated noise component, and is valid whether the break is known or unknown.

Table 3.4 shows the test statistics of Perron and Yabu (2009b), the estimated break date and the integration before and after the break dates. The break dates are obtained by minimizing the sum of squared residuals from the regression of the stock market integration on a constant, a deterministic trend, a level-shift dummy and a slope-shift dummy.<sup>19</sup> Interestingly, while Austria, Japan and Switzerland all have significant breaks in their integration measure, these markets lack trends in the integration. This echoes our thought that the trend test in Table 3.3 may be weakened by the breaks. For some of the Euro-zone countries such as France and Italy, the break dates are significant around January 1999, the time when the euro was introduced, reflecting its sizable impact upon financial markets. In addition, integration break dates are all around 2008, for the United States, Canada, Germany, Japan, Netherlands and Spain, shedding light on the importance of the global financial crisis on integration.

We further exploit the differences of integration before and after the break dates in Table 3.4. The integration after the break appears to be greater than before. Take Japan as an example, its average integration index jumps to 0.30, twice as large as the level of integration before the estimated break date 2007Q4, which is around the financial crisis in 2008. Additionally, by applying

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<sup>19</sup>According to Perron and Zhu (2005), this break date selection generates a consistent estimate regardless whether the noise component is stationary or integrated.

a simple  $t$  test with Newey-West error, we strongly reject the null hypothesis that the mean before the breaks are larger than that after, at the 5% significance level across different countries.<sup>20</sup> We conclude that the estimated integration series are of a substantially greater magnitude after the break dates. In other words, financial integration has increased structurally among advanced economies and cross-country diversification has decreased around the world. Therefore, the lack of significant trends in cross-country integration for some countries is likely due to the structural breaks, confirming the argument that integration is changing over time and reflecting the setting of time-varying factor exposures and risk in our model.

## **3.6 What Drives Financial Integration?**

This section focuses on the statistic and economic mechanisms that drive international financial integration. We first decompose the integration measure to investigate trends in the global and local components. Then, we predict the integration measure using macroeconomic fundamentals identified by the literature, in particular the VIX index, and verify which variables are informative about the evolution of integration.

### **3.6.1 Decomposing the Integration Measure**

After studying the features of our integration measure, we aim to understand the statistical and economic mechanisms behind the cross-country differences and trends in integration. Our method is advantageous as we are able to trace the systematic risk of global factor, local factor and estimation error over time and examine which components are the drivers of financial integration.

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<sup>20</sup>We report the test statistics in the appendix.

As discussed in Section 3.2.2, rising financial integration can be caused by increasing risk due to the global factor and/or decreasing risk due to the country factor and estimation error. We present trend tests for these three elements in absolute terms in Table 3.5, to underscore the channels through which integration has varied across countries.<sup>21</sup> We uncover that the upward trends in financial integration are mainly a result of increasing global risk, with positive and significant trends coefficients of large magnitudes for most of the countries. For instance, in Table 3.5, Hong Kong has a large trend coefficient for global risk, consistent with it having the greatest degree of integration among the economies we study. Interestingly, for countries such as Australia, Germany and Netherlands on the one hand, the positive effect of increasing global factors is further amplified by decreasing local risk and estimation risk, leading to greater integration. On the other hand, the rest of the countries have sizable local and estimation risk, which reduce financial integration. Importantly, this negative effect is largely offset by the positive effect generated from growing global risk, resulting in the upward trends in integration. Therefore, we conclude that it is mainly the increasing global factors that drive the dynamics of integration. These results highlight the importance of investigating and understanding all determinants of integration.

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<sup>21</sup> Eiling and Gerard (2014) decompose the emerging equity market comovements, but they focus on the global risk, regional and country-level risk channels.

### **3.6.2 Determinants of Financial Integration**

To further understand the economic mechanisms that affect integration, our paper provides formal evidence about the predictability of financial integration based upon economic fundamentals. This attempt to predict integration has potential implications concerning investors, as increasing financial integration causes decreasing international portfolio diversification benefits (Driessen and Laeven (2007), Bekaert et al. (2009), and Donadelli and Paradiso (2014)). With respect to policymakers, a robust and integrated future financial market contributes to the smooth transmission of monetary policy. Furthermore, one should be also be aware of the spillovers and contagion risk generated from integrated financial markets. Cerutti et al. (2017) argue that further work on integration could be done by introducing intrinsic dynamics in global financial cycles and evaluating their magnitudes using out-of-sample statistical techniques. This explicitly echos our financial integration prediction exercise. Particularly, by applying a flexible Bayesian forecasting model developed by Dangl and Halling (2012) and Koop and Korobilis (2012), we are able to understand the importance of possible determinants of financial integration over time, and the differences between each country's integration process. To the best of our knowledge, this is the first study in the literature that systematically forecasts financial integration using different macroeconomic predictors.

#### **3.6.2.1 Construction of Macroeconomic Predictors**

In this section, we discuss the potential macroeconomic predictors for financial integration. Our first potential determinant of financial integration is international trade. As trade increases economic ties between countries, such as cash flows, this may lead to an increasing link between their equity markets. We, therefore, expect trade openness to positively affect financial integration.

Usually, the trade channel links to international spillovers or contagion (see, Caramazza et al. (2004) and Baele and Inghelbrecht (2009) for examples). Similar to, among others, Carrieri et al. (2007) and Eiling and Gerard (2014), we measure trade openness as the ratio of imports and exports over nominal GDP in US dollars. Quarterly trade and GDP data are obtained from the IMF.

Second, we consider investment openness. A higher level of investment openness lessens restrictions encountered by investors from foreign countries and leads to greater stock market integration. According to Bekaert et al. (2002), stock market integration tends to lag financial reforms as liberalization always takes time to be effective. Thus, investment openness could be a predictor of integration. We measure investment openness as the ratio of FDI assets plus FDI liabilities over nominal GDP in dollars. FDI data is from the International Financial Statistics database based on the IMF.

Third, following Eiling and Gerard (2014), we assess relevance of the growth in real per capital GDP as a proxy of economic growth. Real per capital GDP data comes from the IMF, World Bank, Eurostat and the OECD databases. Fourth, as Longin and Solnik (2001) and Forbes and Rigobon (2002) clearly find evidence that linkages between different financial markets increase in time of stress due to heteroskedasticity volatility, we include a business cycle variable: the NBER recession dummy.<sup>22</sup>

Last, we consider VIX, the Chicago Board Options Exchange (CBOE) Volatility Index, which is viewed as a measure of risk aversion and fear in financial markets. Rey (2015) uncovers that there exists a global financial cycle in risky assets around the world, which can be interpreted as the effective risk appetite of the market and realized world market volatility. It is therefore expected that this global cycle is related to the VIX index (Miranda-Agrippino and Rey

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<sup>22</sup>We also consider the OECD based recession indicator, which is available for most of the countries except Hong Kong, Singapore and the United States. The results are qualitatively similar.

(2015) and Rey (2015)). In our paper, we extract global factors from stock markets and use these factors to construct financial integration measures for each economy. We, thus, expect VIX could affect our financial integration measure and believe that this is the first work that studies the relationship between VIX and financial integration.

For most of the countries, the out-of-sample period starts from 1990Q1. Exceptions are Singapore, for which the sample starts from 1995Q1, Japan, sample starts from 1996Q1, Hong Kong and Switzerland, sample starts from 1999Q1. Belgium and Austria have short sample periods, beginning from 2002Q1 and 2005Q1 respectively.

### 3.6.2.2 Dynamic Linear Models

In this section, instead of the OLS regressions, dynamic linear models are set up following Dangl and Halling (2012) to predict cross-country integration. This is because a large number of researchers have suggested that time-variation in coefficients would improve forecast performance.<sup>23</sup> While dynamic models capture the time-varying nature of financial integration and macroeconomic explanatory variables, constant coefficients ignore the problem of parameter instability. Here we strictly perform an out-of-sample predictive performance, in the sense that we only use available information at/or before time  $t$  to forecast the integration at time  $t + 1$ . Particularly, the linkage between integration  $TVI_{t+1}$  and its determinants  $Z_t$  is captured using the following model:

$$TVI_{t+1} = Z_t' \theta_t + v_{t+1}, \quad v \sim N(0, V) \quad (\text{observation equation}) \quad (3.7)$$

$$\theta_t = \theta_{t-1} + \omega_t, \quad \omega \sim N(0, W_t) \quad (\text{system equation}) \quad (3.8)$$

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<sup>23</sup>See, for example, Dangl and Halling (2012) in the context of stock returns and Byrne et al. (2018) for exchange rate prediction.



where the vector  $Z_t$  contains possible combinations of the predictors,  $\theta_t$  is the vector of time-varying coefficients which are composed to random shocks with variance matrix  $W_t$  and  $V$  is the unknown observational variance.

Let  $D_t = [TVI_t, TVI_{t-1}, \dots, Z_t, Z_{t-1}, \dots]$  denote the information available at time  $t$ . The posteriors of the coefficients follow a multivariate  $t$ -distribution:

$$\theta_{t-1} \mid D_t \sim T_{n_t}[\hat{\theta}_t, S_t C_t^*] \quad (3.9)$$

where  $S_t$  is the mean of the estimated  $V$  at time  $t$  and  $C_t^*$  is the estimated conditional covariance matrix of  $\theta_{t-1}$  normalized by the observational variance. When iteratively updating the coefficients, they are exposed to Gaussian shocks  $W_t$ :

$$\theta_t \mid D_t \sim T_{n_t}[\hat{\theta}_t, R_t], \quad R_t = S_t C_t^* + W_t \quad (3.10)$$

Instead of specifying  $W_t$ , we apply a discount factor approach to ease computational demands:

$$R_t = \frac{1}{\delta} S_t, \quad \delta \in \delta_1, \delta_2, \dots, \delta_d, \quad 0 < \delta_k \leq 1 \quad (3.11)$$

Therefore, models with constant coefficients correspond to a specification of  $\delta = 1$ . Whereas, setting  $\delta$  below 1 implies coefficients are time-varying. As the choice of degree of variability in coefficients influences the predictive density of the dynamic linear models, we need to choose the range of  $\delta$ . In general, we assume  $\delta \in [0.90, 1]$ .<sup>24</sup> When  $\delta=0.99$ , the variance of the coefficient will increase 18% within five years. Whereas, for  $\delta=0.90$ , this increase will jump to 88%. The latter case suggests the coefficients change rapidly and, therefore, we set it as the lower bound. We provide more details about dynamic linear models in the appendix.

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<sup>24</sup>Specifically,  $\delta = [0.90, 0.91, 0.92, 0.93, 0.94, 0.95, 0.96, 0.97, 0.98, 0.99, 1]$ .

### 3.6.2.3 Dynamic Model Averaging

Since this is the first study to examine the predictors of financial integration, there is considerable uncertainty as to which indicators contain useful information. Indeed, even though we introduce dynamics in the linear model, there is still high uncertainty regarding the choice of predictive variables.<sup>25</sup> The chapter appendix provides more details about the dynamic model averaging (DMA) proposed by Raftery et al. (2010) and Koop and Korobilis (2012).

Generally, the DMA allows for the weights attached to each dynamic linear model to change based upon their past forecasting performances, in a way that the entire forecasting model is time-varying. In particular,  $\alpha$  is the forgetting factor that controls the degree of time-variation in forecasting models, see Raftery et al. (2010), Koop and Korobilis (2012) and Byrne and Fu (2017) for more details. For example,  $\alpha = 0.95$  means that forecast performance five years ago only receives 36% weight than that last quarter. When  $\alpha = 0.99$  this number increases to 82%. When  $\alpha = 1$ , DMA shrinks to normal Bayesian model averaging (BMA) and when  $\alpha = 0$ , each model has the same weight over time. Here we fix  $\alpha = 0.99$  with modest change in the forecasting models. In sum, we take the uncertainty of time-variation in coefficients, in addition to the uncertainty of predictors into account when conducting the forecasting practice.

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<sup>25</sup>For instance, assume we have  $m$  candidate indicators (including the constant), this implies  $2^m - 1$  possible linear regression models. Considering  $d$  kinds of the presumed variability in the coefficients  $\theta_t$  leads to a total of  $d \cdot (2^m - 1)$  possible dynamic linear models. Following Dangi and Halling (2012) and Koop and Korobilis (2012), we assign diffuse prior for each model at first (i.e.,  $1/(d \cdot (2^m - 1))$ ) and the posterior probabilities of these models are updated quarter by quarter according to Bayes rule.

#### 3.6.2.4 Forecast Results

As mentioned above, we forecast financial integration using trade, FDI, growth, the NBER recession dates and the VIX index. We focus on the importance of the VIX on predicting integration, since Rey (2015) suggests this is a key driver of the financial cycle. Therefore, we compare forecast results using the DMA which includes VIX as a predictor and the DMA without VIX, while keeping other predictors the same in the predictive regressions.

In terms of forecast evaluation, we first compute the Relative Mean Squared Forecast Error (RMSFE) of DMA compared to driftless Random Walk (RW) to measure forecast performance. Values below one indicate that DMA performs better than RW. The RW is well known to be a strict out-of-sample benchmark, which excludes predictors and only includes a constant term with constant coefficient in the regressions. To evaluate the statistical differences in forecast, the Clark and West (2007) (CW) test is employed under the null hypothesis that the MSFE of RW is less than or equal to that of DMA.<sup>26</sup> The last criteria we use is the log Predictive Likelihood difference between DMA and RW ( $\Delta\log(\text{PL})$ ). Values above zero imply that this specification has larger predictive likelihood and it has better forecasts in a Bayesian comparison.

Table 3.6 shows the forecast performance of the DMA compared to the RW. The overall story is clear: the time-varying integration we derive is highly predictable, as the DMA with VIX and the one without VIX both largely and significantly outperform RW almost for all the countries we consider. Take Italy as an example when VIX is considered, the reduction in the RMSFE reaches 63%, with the CW test being rejected at the 1% significance level, and the difference in predictive likelihood 37.50. These findings have important implications for

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<sup>26</sup>One advantage of the CW test is that it still follows an asymptotically standard normal distribution when comparing with the predictive results of nested models. This is exactly our case as RW is nested in our general DMA model.

investors due to the fact that increasing integration implies decreasing international diversification. Therefore, investors could manage risk and adjust portfolio allocation, based on the prediction of the financial market integration cross-country.

We also find that although DMA's prediction of integration without VIX also dominates RW, including VIX as a predictor can improve forecast results. In particular, compared to the DMA without VIX, the RMSFE of DMA with VIX for each country is larger and the predictive likelihood of it is smaller. This extends the finding in Miranda-Agrippino and Rey (2015) that VIX interacts with the global factor. We conclude that VIX, which is constructed using the implied volatilities of a wide range of S&P 500 index options, is informative about the movements of financial integration for each country, reflecting the argument that international financial system is more vulnerable to the shocks and uncertainty that originate from the center economies such as the United States.

It is well known that the prediction results can be contaminated if there exists the problem of reverse causality. Therefore, to check whether financial integration reversely predict movements of the VIX index, we further employ the pair-wise Granger causality test between financial integration and the VIX index for different countries in the appendix. Importantly, according to Table B.5, we find that for all the countries we consider, we cannot reject the null hypotheses that integration does not Granger cause VIX. Nevertheless, the hypotheses that VIX does not Granger cause integration can be strongly rejected, except for three Asian economies: Hong Kong, Japan and Singapore. This echoes to the finding that Hong Kong and Japan especially have different integration dynamics compared with others and is also in line with the argument that VIX is a powerful predictor for financial integration.

Interestingly, the literature argues that in a perfect and frictionless economy, individual stock prices reflect changes about future cash flows and discount rates. Thus, firm-level stock prices should move together due to economic fundamentals. However, in a world with frictions and irrational investors, comovement in stock prices tend to isolate from fundamentals explained by the “friction-based” and “sentiment-based” theories (Pindyck and Rotemberg (1993) and Boyer (2011)). We argue that time-variation in coefficients and in models could account for some degrees of the financial integration from an aggregate stock return perspective. This is analogous to the finding of Chen et al. (2016) that changes in loadings on the fundamentals relieve the evidence of excess comovement for individual stocks.

#### **3.6.2.5 Time-varying Prediction Inclusion Probabilities**

With changes in regulations and economic structures, the role of different variables in predicting financial integration would also change over time. We therefore present the time-varying posterior inclusion probabilities for each predictor across different countries. Higher inclusion probabilities imply higher predictor importance and demonstrate different characteristics of integration predictability cross-country.

Figure 3.3 depicts the time-varying inclusion probabilities for different predictors. The prior of inclusion probability is 0.5 as there is equal chance that this predictor is included or not. While a higher inclusion probability implies a better predictive power, we find that financial integration for different countries has different determinants and their importance evolves over time. Therefore, it would be less appropriate to employ simple pooled cross-sectional time-series regressions and time-series regressions following Carrieri et al. (2007) and Eiling and Gerard (2014).

We uncover from Figure 3.3 that the VIX index becomes increasingly important at the end of the sample period, with its inclusion probability almost one for G7 and European countries. Trade openness is also highly informative about movements for most of the financial integration series. Additionally, we find some evidence suggesting that real GDP per capital affects integration, especially for Denmark, France, Hong Kong, Japan, Singapore, Spain and the United Kingdom. Whereas, investment openness is less crucial as its inclusion probabilities quickly become negligible after the initial data points, except for Japan around 2005, Netherlands around 2000 and the United Kingdom during the recent financial crisis.

Take Japan as an illustration to see how the importance of predictors changes over time. Trade openness and real GDP per capital are initially influential. FDI marginally affects integration between 2000 to 2008 and the inclusion probability for NBER over the whole sample period is negligible. The importance of real GDP per capital declines and inclusion probability for investment openness spikes around 2008. From 2010, the VIX index gains support from the data and is included in the predictive regression. Interestingly, we notice that the inclusion probabilities of all the predictors for Austria are low after the initial data adjustment, reflecting the fact that it is the only country that fails to outperform the RW for the whole sample period.

To summarize the way in which macro fundamentals affect integration over the whole sample period, we present the average inclusion probabilities for each predictor across countries. We also provide the average inclusion probabilities for G7 countries and for all the countries we consider. Generally, the main determinant of cross-country financial integration is our proxy for market volatility and risk aversion: the VIX index, with overall average inclusion probability of 0.38. Trade openness is the second strong predictor for

integration.<sup>27</sup>

To investigate the possibility that the predictability of the VIX index is only associated with the variance of global factors, in Table B.6, we further present the predictor inclusion probabilities for the financial integration derived from constant factor loadings and risk, where the integration variation is mainly induced by the variance of global factors. We find that the inclusion probabilities for all the predictors drop compared to baseline results. This indicates that our prediction practice is meaningful and VIX captures financial integration dynamics on top of the volatility of global factors.

Miranda-Agrippino and Rey (2015) point out that the gains of international financial integration could be less than the risks due to volatile capital flows driven by extreme events occurred in center economies such as the United States. We confirm this statement as VIX dominates other integration drivers in general. This provides insights that peripheral countries may choose to insulate themselves from global comovements by introducing macro-prudential policies and self-insurance mechanisms, consistent with the findings of Blanchard et al. (2010).

### 3.7 Conclusion

It is crucial to accurately measure financial integration both for academic research and policy making. A natural approach to measure integration is by applying an International Capital Asset Pricing Model model (ICAPM), in the sense that if the stock returns of different countries can be fully explained

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<sup>27</sup>This is consistent with the finding in Eiling and Gerard (2014) that trade openness affects integration measure.

by the same global factors, they are perfectly integrated. However, a common assumption of using ICAPM to measure integration is that both the factor loadings and the stochastic volatility in the factor model are constant over time, and consequently it is unable to capture short run transitory and long run structural changes in the integration measure.

In this paper, therefore, we incorporate time-variation in factor exposures and volatility within an ICAPM model to construct financial integration. Specifically, we first apply principal component analysis to capture the financial market global factors. We then set up a model which decomposes stock returns into country-specific effects and global factors using time-varying coefficients and stochastic volatility. Finally, the time-varying financial integration is calculated as the percentage of total return variance explained by the global factors.

We uncover that financial integration is generally increasing, although financial liberalization policies stall and reverse. In contrast to other *de jure* financial openness measures such as Chinn and Ito (2008) and Abiad et al. (2010), none of the advanced economies in our sample consistently achieve full financial integration, as even for fully liberalized markets, investors still prefer investing at home due to the home bias puzzle. Financial integration reaches local maxima during the financial crisis in 2008. However, while global factors are relevant in explaining time variation of cross-market integration, the country-specific effect still prevails.

Importantly, we find that time-varying factor loadings and stochastic volatility matter when measuring integration. In particular, by testing time-variation in the factor loadings and comparing our integration measure to that drawn from constant factor loadings and risk under the ICAPM framework, we show that factor loadings are time-varying and the simple ICAPM cannot reveal the linkages between different financial markets. We further check whether time



trends and/or breaks exist in the time-varying integration and find that financial integration increased structurally in recent decades, consistent with the perception that financial markets are more connected due to the development of financial liberalization and capital mobility.

Finally, we illustrate that the upward trend in integration is mainly driven by increasing global comovement instead of decreasing local effects. Furthermore, integration is highly predictable by combining different dynamic linear models using macroeconomic predictors. The importance of each predictor evolves distinctly across different markets. Generally, the VIX index is highly informative about movements of integration for most economies. This is consistent with the view that financial integration is predominantly driven by shocks from the financial market.

TABLE 3.1: Summary Statistics For Financial Integration

	Mean	Median	Stdev	Min	Max	Skew	Kurt	$\rho(1)$	$\rho(2)$	$p_{ADF}$
Australia	0.37	0.36	0.13	0.12	0.77	0.45	2.99	0.71	0.59	0.13
Austria	0.32	0.31	0.13	0.07	0.71	0.41	2.79	0.74	0.64	0.09
Belgium	0.19	0.17	0.10	0.05	0.53	0.93	3.67	0.71	0.57	0.02
Canada	0.37	0.36	0.12	0.12	0.74	0.57	3.36	0.67	0.52	0.12
Denmark	0.29	0.26	0.14	0.04	0.80	1.03	4.24	0.64	0.48	0.02
France	0.38	0.33	0.18	0.11	0.92	0.79	2.97	0.73	0.63	0.05
Germany	0.39	0.39	0.13	0.11	0.79	0.30	2.94	0.72	0.61	0.17
Hong Kong	0.67	0.70	0.15	0.15	0.98	-0.92	4.14	0.73	0.62	0.39
Italy	0.44	0.45	0.16	0.15	0.89	0.24	2.44	0.76	0.65	0.15
Japan	0.18	0.15	0.12	0.03	0.61	1.60	5.41	0.69	0.51	0.00
Netherlands	0.40	0.40	0.14	0.12	0.82	0.35	3.06	0.74	0.64	0.18
Norway	0.47	0.48	0.15	0.11	0.87	-0.05	2.87	0.71	0.57	0.16
Singapore	0.50	0.52	0.17	0.15	0.89	-0.02	2.51	0.75	0.66	0.20
Spain	0.53	0.53	0.14	0.15	0.88	-0.17	2.92	0.67	0.56	0.23
Sweden	0.38	0.38	0.14	0.08	0.85	0.42	3.07	0.70	0.57	0.10
Switzerland	0.45	0.44	0.17	0.10	0.90	0.47	2.97	0.71	0.59	0.12
United Kingdom	0.40	0.37	0.17	0.07	0.86	0.52	2.71	0.73	0.63	0.07
United States	0.46	0.47	0.13	0.17	0.83	0.12	2.96	0.63	0.47	0.14

*Notes:* This table reports the summary statistics for financial integration.  $\rho(1)$  and  $\rho(2)$  represent autocorrelation coefficients for one and two lags.  $p_{ADF}$  shows the  $p$  values of the Augmented Dickey-Fuller test for a unit root with an intercept and a time trend, where the optimal number of lags is determined by Bayesian Information Criterion. The null hypothesis is that there exists a unit root in the financial integration series. The sample period is from 1971Q1 to 2017Q1.

TABLE 3.2: Elliott-Müller Test for Time-varying Factor Loadings

	<i>Test stat.</i>		<i>Test stat.</i>
Australia	-57.47***	Japan	-65.42***
Austria	-148.39***	Netherlands	-60.80***
Belgium	-62.12***	Norway	-112.15***
Canada	-67.83***	Singapore	-57.27***
Denmark	-68.40***	Spain	-63.17***
France	-48.90***	Sweden	-115.55***
Germany	-72.28***	Switzerland	-42.56***
Hong Kong	-96.32***	United Kingdom	-43.51***
Italy	-97.43***	United States	-28.06***

*Notes:* This table reports the Elliott and Müller (2006) test statistics to detect time-variation in factor loadings. The null hypothesis is that factor loadings are fixed over the sample period. Hence rejection of the null implies that the parameters are time-varying. The 1%(\*), 5%(\*\*) and 10% (\*\*\*) critical values are -23.42, -19.84 and -18.07 respectively. The sample period is from 1971Q1 to 2017Q1.

TABLE 3.3: Financial Integration Trend Tests

	<i>Trend</i>	<i>t test</i>		<i>Trend</i>	<i>t test</i>
Australia	1.51%	4.00***	Japan	0.42%	0.25
Austria	1.44%	0.52	Netherlands	1.91%	4.58***
Belgium	1.12%	2.92***	Norway	1.73%	2.44**
Canada	1.37%	3.06***	Singapore	2.71%	1.63
Denmark	1.22%	3.39***	Spain	2.01%	3.86***
France	2.23%	4.38***	Sweden	1.71%	2.35**
Germany	1.85%	4.26***	Switzerland	0.26%	1.15
Hong Kong	3.49%	4.29***	United Kingdom	2.10%	2.45**
Italy	2.25%	2.86***	United States	1.39%	2.62***

*Notes:* This table reports the estimated trend coefficients in percentages based on the Perron and Yabu (2009a) test in the financial integration series. The null hypothesis is that there is no trend in the integration. Following a normal distribution, the 1%(\*), 5%(\*\*) and 10% (\*\*\*) critical values of these two-sided tests are 1.65, 1.96 and 2.58 respectively.

TABLE 3.4: Financial Integration Break Tests

	$W_{RQF}$	$T_{Break}$	<i>Before</i>	<i>After</i>
Australia	1.20	1998Q2	0.30	0.47
Austria	8.40***	1984Q4	0.29	0.34
Belgium	4.85***	2002Q2	0.14	0.28
Canada	1.27	2008Q2	0.34	0.49
Denmark	1.01	2000Q3	0.27	0.33
France	3.00*	2000Q3	0.33	0.47
Germany	1.26	2008Q2	0.36	0.54
Hong Kong	4.11**	1986Q3	0.57	0.73
Italy	2.60*	1998Q2	0.35	0.58
Japan	5.00***	2007Q4	0.15	0.30
Netherlands	1.41	2007Q4	0.36	0.56
Norway	0.57	1979Q1	0.36	0.49
Singapore	1.14	1984Q4	0.37	0.56
Spain	0.75	2008Q2	0.50	0.66
Sweden	2.97*	1996Q4	0.31	0.48
Switzerland	4.22**	2000Q3	0.42	0.52
United Kingdom	3.90**	2000Q3	0.36	0.48
United States	0.71	2008Q2	0.44	0.58

*Notes:* This table shows the break test of Perron and Yabu (2009b) and the average integration index before and after break dates.  $W_{RQF}$  represents Perron and Yabu (2009b) test statistics and  $T_{Break}$  shows the dates of the breaks. *Before* and *After* represent the level of financial integration before and after its corresponding break dates. The specification of the break test includes a constant and a time trend. The critical values for  $W_{RQF}$  are 2.48, 3.12 and 4.47 at the significance level of 10%(\*), 5%(\*\*) and 1%(\*\*\*) respectively.

TABLE 3.5: Trend Tests for the Components of Integration Measure

	Global Risk		Country Risk		Estimation Risk	
	<i>Trend</i>	<i>t test</i>	<i>Trend</i>	<i>t test</i>	<i>Trend</i>	<i>t test</i>
Australia	7.81%	1.91*	-0.43%	-0.60	-2.99%	-3.01***
Austria	4.59%	2.73***	-0.13%	-0.76	0.63%	0.12
Belgium	0.68%	2.07**	-0.04%	-0.90	0.09%	0.12
Canada	5.20%	1.97**	-0.55%	-1.00	0.25%	0.52
Denmark	2.48%	0.21	2.28%	1.07	1.42%	1.53
France	8.45%	0.39	2.82%	1.75*	0.16%	0.08
Germany	5.77%	2.13**	-0.44%	-1.25	-1.99%	-5.08
Hong Kong	40.60%	3.78***	8.32%	1.78*	-1.35%	-1.07
Italy	7.91%	1.98**	0.76%	8.86***	-2.13%	-1.16
Japan	0.44%	0.10	0.31%	9.29***	0.79%	0.08
Netherlands	4.79%	2.41**	-0.20%	-0.80	-0.87%	-4.00***
Norway	9.38%	1.93*	0.95%	8.84***	-1.87%	-1.44
Singapore	11.73%	3.12***	0.40%	5.96***	-2.96%	-1.90*
Spain	18.82%	2.42**	1.08%	5.22***	-2.93%	-4.01***
Sweden	4.13%	1.85*	0.42%	7.89***	-0.22%	-0.17
Switzerland	5.31%	0.16	0.52%	11.52***	-1.26%	-1.88*
United Kingdom	4.80%	0.22	0.55%	14.49***	0.23%	0.11
United States	6.19%	1.89*	0.59%	7.59***	-0.68%	-1.64

Notes: This table reports the trend tests for the variance due to the global factors  $\beta_{i,t}^p$  (global risk), the country-specific factor  $\mu_{i,t}$  (country risk) and the stochastic volatility  $h_{i,t}$  (estimation risk) when constructing integration measure. \*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% levels. See more details about the trend test in Table 3.3.

TABLE 3.6: Forecast Evaluation

	DMA with VIX		DMA without VIX	
	<i>RMSFE</i>	$\Delta\log(PL)$	<i>RMSFE</i>	$\Delta\log(PL)$
Australia	0.41***	28.72	0.44***	25.02
Austria	0.97	0.00	0.98	-0.04
Belgium	0.99*	-0.52	0.99*	-0.52
Canada	0.56***	21.45	0.67***	13.40
Denmark	0.80**	8.30	0.88*	5.11
France	0.63***	9.81	0.69*	5.61
Germany	0.38***	34.85	0.51***	24.64
Hong Kong	0.89***	2.27	0.89***	2.28
Italy	0.37***	37.50	0.49***	25.88
Japan	0.59**	22.02	0.79*	12.28
Netherlands	0.52***	27.51	0.62***	20.02
Norway	0.53***	18.00	0.68***	10.85
Singapore	0.67***	9.11	0.78***	5.98
Spain	0.68***	12.36	0.74***	10.48
Sweden	0.46***	29.30	0.49***	28.92
Switzerland	0.66***	9.69	0.74***	7.25
United Kingdom	0.79***	10.24	0.82***	8.06
United States	0.70***	12.19	0.80***	7.29

*Notes:* Forecast evaluation for time-varying integration using different predictors compared to driftless Random Walk (RW), the benchmark model. Specially, we consider two scenarios: DMA including VIX as a predictor and those excluding VIX. Forecast measures include the Relative Mean Squared Forecast Error (RMSFE),  $p$  values for Clark and West test and the difference of log Predictive Likelihood ( $\Delta\log(PL)$ ). Asterisks (\*10%, \*\*5%, \*\*\*1%) relate to the Clark and West test under the null hypothesis that the MSFE of the RW is less than or equal to that of the DMA model.

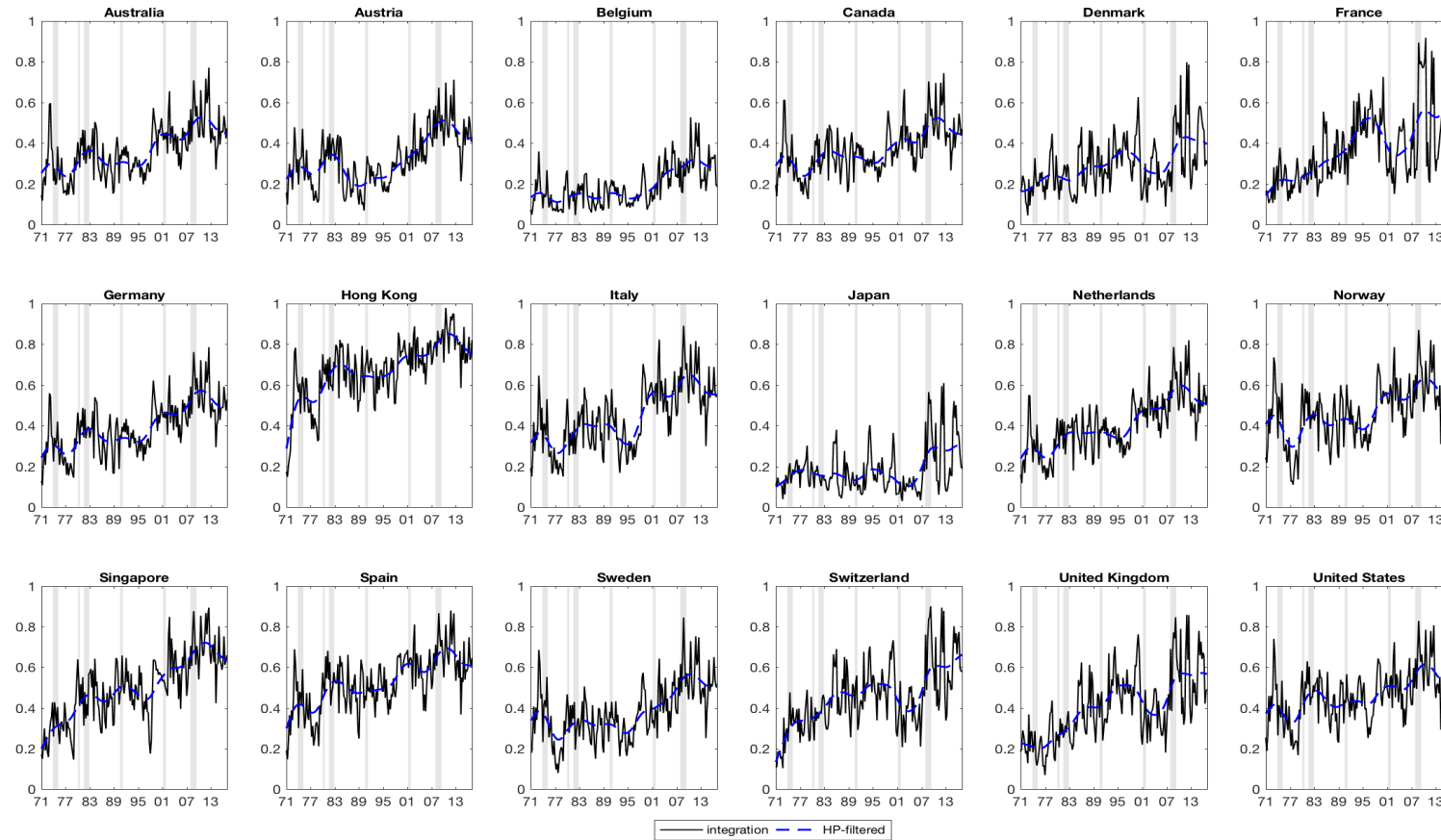
TABLE 3.7: Average Inclusion Probabilities for Different Predictors

	VIX	FDI	Growth	NBER	Trade
Australia	0.60	0.02	0.02	0.03	0.33
Austria	0.05	0.03	0.04	0.14	0.14
Belgium	0.03	0.02	0.04	0.22	0.09
Canada	0.52	0.03	0.02	0.04	0.19
Denmark	0.28	0.02	0.13	0.06	0.42
France	0.25	0.02	0.26	0.06	0.36
Germany	0.45	0.02	0.01	0.04	0.64
Hong Kong	0.05	0.01	0.31	0.08	0.07
Italy	0.67	0.02	0.06	0.05	0.36
Japan	0.38	0.11	0.31	0.14	0.76
Netherlands	0.43	0.04	0.03	0.04	0.29
Norway	0.75	0.02	0.03	0.05	0.26
Singapore	0.37	0.01	0.19	0.16	0.12
Spain	0.35	0.02	0.12	0.05	0.38
Sweden	0.60	0.01	0.04	0.04	0.40
Switzerland	0.38	0.02	0.05	0.13	0.28
United Kingdom	0.18	0.04	0.47	0.05	0.28
United States	0.43	0.05	0.03	0.05	0.35
G7	0.41	0.04	0.17	0.06	0.42
Overall average	0.38	0.03	0.12	0.08	0.32

*Notes:* This table presents the average inclusion probabilities for different predictors over the corresponding sample periods. The higher the inclusion probabilities, the more important the predictors are on predicting integration. The description of the predictors is as follows: FDI refers to investment openness, Growth refers to real GDP per capita, NBER refers to NBER recession dummy, Trade refers to trade openness and VIX refers to the Chicago Board Options Exchange (CBOE) Volatility Index. We also summarize the average inclusion probabilities for G7 countries and for all the countries we consider.

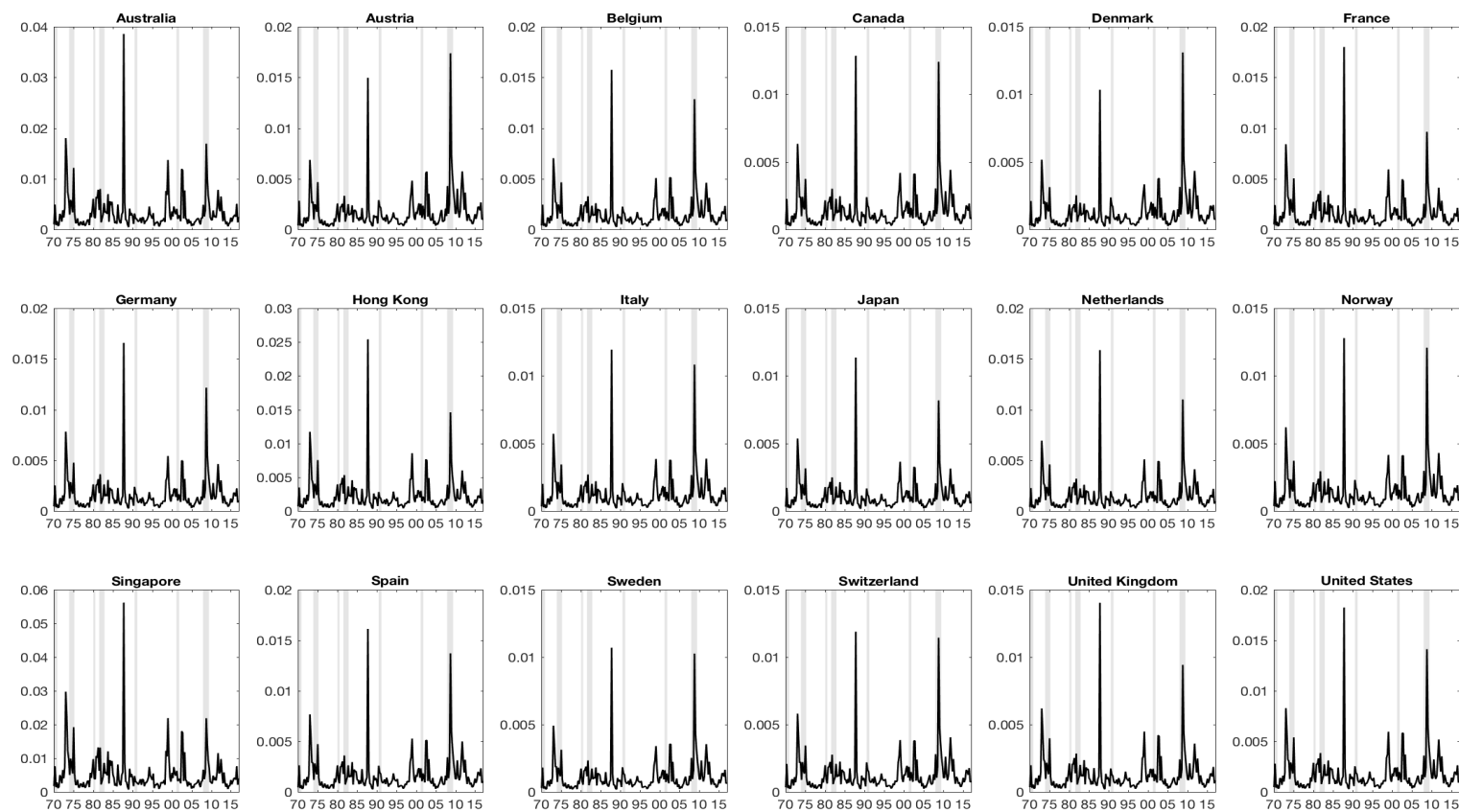


FIGURE 3.1: Measure of Financial Integration Based Upon ICAPM Model



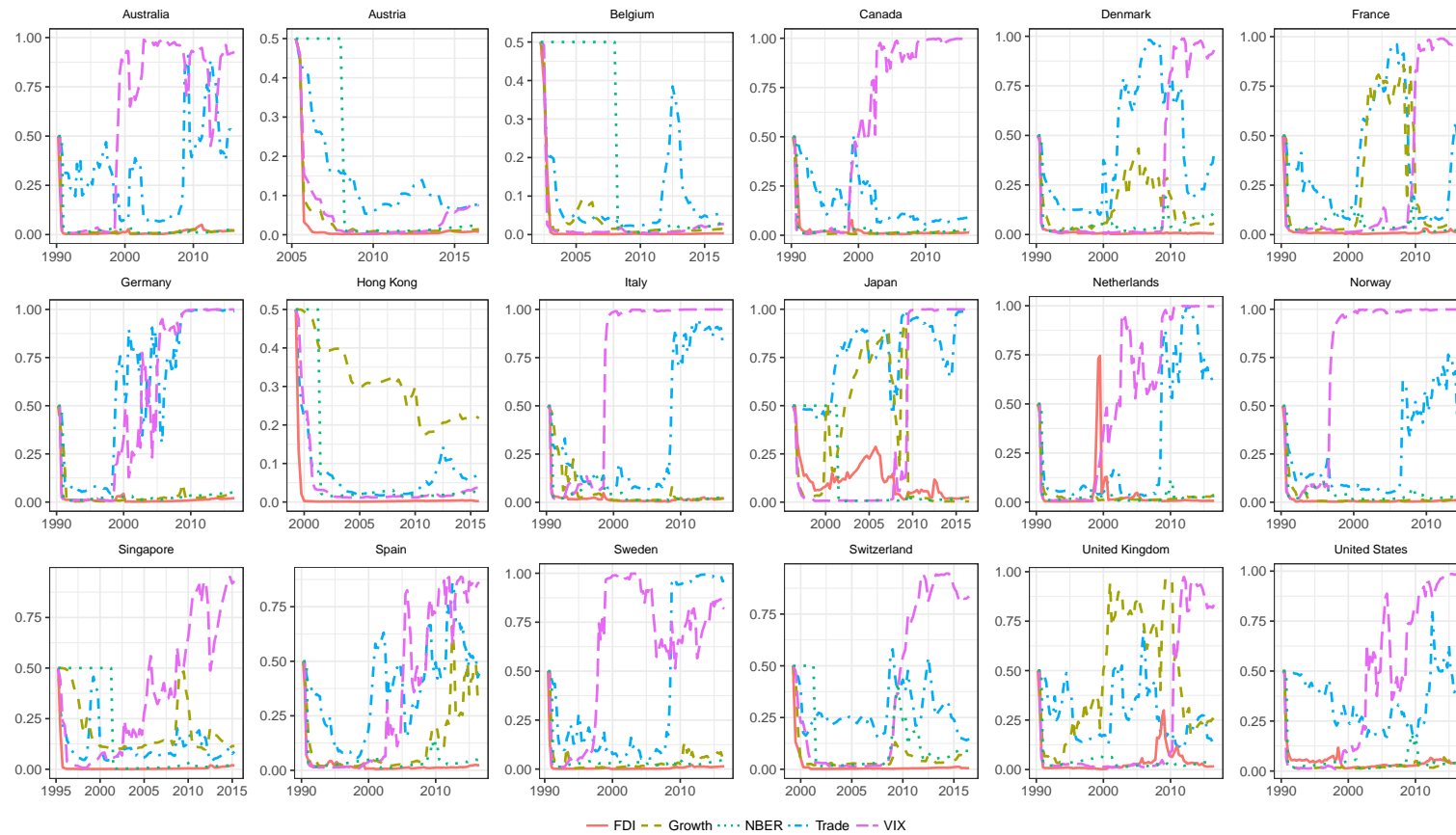
*Notes:* This figure shows the time-varying integration measure we derive based on the fraction of total return variance explained by global factors cross-country. The solid line is the financial integration, the dashed line is the H-P filtered trend of integration and the shaded areas are the NBER recession dates.

FIGURE 3.2: Financial Integration Derived from Constant Factor Loading and Risk



*Notes:* This figure shows the time-varying integration derived from the simple international CAPM, with constant factor loading and constant volatility in Equation (3.4). The shaded areas are the NBER recession dates.

FIGURE 3.3: Time-Varying Inclusion Probabilities for Different Predictors



*Notes:* The figure shows time-varying inclusion probabilities for different predictors cross-country. The description of the predictors is as follows: FDI refers to investment openness, Growth refers to real GDP per capita, NBER refers to NBER recession dummy, Trade refers to trade openness and VIX refers to the Chicago Board Options Exchange (CBOE) Volatility Index.

## Chapter 4

# Financial Uncertainty and the Effectiveness of Monetary Policy

### 4.1 Introduction

The recent financial crisis has sparked great interest in studying financial fluctuations and their impact on the economy. For instance, Ng and Wright (2013) argue that all the post-1982 recessions originate from shocks to financial markets. Ludvigson et al. (2015) address the importance of financial uncertainty by suggesting that financial shocks are likely to cause business cycle fluctuations, while uncertainty about economic activity is likely to be an endogenous response to other shocks.<sup>1</sup> Although the literature has suggested financial uncertainty could play a key role in recessions, both as an origin and as a propagating mechanism, there has been little research on identifying whether financial uncertainty influences the effects of other structural shocks, especially how it affects the transmission mechanism of monetary policy on the economy.<sup>2</sup>

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<sup>1</sup>A similar message is delivered by Caldara et al. (2016), who suggest that financial uncertainty is a key source of business cycle fluctuations since the mid-1980s. Stock and Watson (2012) also find that financial disruptions are one of the main contributors to the 2007-2009 recession.

<sup>2</sup>Another strand of the literature focuses on uncertainty and its impact on the macroeconomy. A nonexclusive list of such studies include Bloom (2009), Jurado et al. (2015), Rossi and

In general terms, there are perceived to be two channels by which monetary policy impacts the real economy: the interest rate and the credit channels. The interest rate channel suggests that policy makers adjust interest rate to affect the cost of raising capital hence demand, economic growth and inflation. While the credit channel posits that the amount of credit in the economy may indirectly amplify monetary policy actions. The theoretical literature has pointed out that the effectiveness of monetary policy on real activity is linked to uncertainty through the nonlinearities in the interest rate and the credit transmission channel. However, researchers have not reached a consensus on how the propagation of monetary policy shocks differ during periods of high and low financial uncertainty periods. In particular, the theory of nonlinearities in the interest rate channel argues that heightened uncertainty could make the economy less sensitive to the federal funds rate. This is as a result of partial irreversibility of investments with real options effects, precautionary savings and uncertainty-dependent price-setting mechanism (Vavra (2013) and Bloom (2014)).<sup>3</sup> There is also theoretical support for nonlinear monetary policy propagation associated with the credit transmission channel. This argument claims that during periods of heightened financial uncertainty, the cost of credit for borrowers reacts stronger to expansionary monetary policy shocks than during tranquil times, see, for example Bernanke et al. (1999), He and Krishnamurthy (2013), and Brunnermeier and Sannikov (2014).<sup>4</sup>

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Sekhposyan (2015), Baker et al. (2016), Carriero et al. (2017) and Mumtaz and Theodoridis (2017). They find that, overall, when an uncertainty shock hits the economy, real aggregate variables generally contract.

<sup>3</sup>Real options effects argue that increasing uncertainty could postpone firms' hire and invest activities, see for example, Dixit et al. (1994), Bloom (2009), Bloom et al. (2012), and Bloom (2014). Precautionary savings theory suggests that uncertainty could lead to higher precautionary savings in the presence of risk averse agents, see, e.g., Bloom (2014). The uncertainty-dependent price-setting mechanism was acknowledged by Vavra (2013), who finds that uncertainty causes firms to adjust price flexibly and consequently monetary policy shocks can lose their effectiveness. These explanations are further explored in Section 4.2.

<sup>4</sup>During periods of financial stress, the external finance premium increases and firms are likely to suffer from liquidity constraints. Therefore, the cost of credit for firms may react

Measuring monetary policy effectiveness during high financial uncertainty periods is of great importance for the central bank.<sup>5</sup> If monetary policy is effective, it can be used as a key tool to alleviate the adverse effects of financial stress on the economy and therefore prevent a more severe recession from happening. Nonetheless, if the monetary policy transmission mechanism is impaired, aggressive and even unconventional monetary policy need to be implemented to stimulate aggregate demand. Failure to be aware of this can weaken the credibility of central banks to keep inflation solidly anchored and increase the cost of interventions, causing excess risk-taking and higher risk of asset price bubbles (Mishkin, 2009; Jiménez et al., 2014; Jannsen et al., 2015).

With these challenges in mind, this paper distinguishes between the effect of high and low financial uncertainty on policy interest rate changes, by modeling the impact of the federal funds rate and various representative macroeconomic and financial variables using the smooth transition vector autoregression (STVAR). The key advantage of STVAR compared to estimated structural VARs for each financial condition is that the smooth transition models effectively extract more information from the data, so that the estimation and inference for each regime is more stable and precise. To assess monetary shocks effects on the dynamics of different variables during high and low financial uncertainty state, the non-linear generalized impulse response functions (GIRFs) and the generalized forecast error variance decomposition are computed following Pesaran and Shin (1998) and Lanne and Nyberg (2016) respectively. GIRFs further takes the possibility that monetary stimulus could ease the tightening financial condition into account. As the transition variable in the STVAR,

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stronger to monetary policy shocks during high financial uncertainty periods compared to normal times with wide internal finance.

<sup>5</sup>Husted et al. (2017) construct a news-based monetary policy uncertainty index, which captures Federal Reserve policy actions and their consequences. They find that positive shocks to the monetary policy uncertainty increase credit spread and reduce output. Investigating the influence of monetary policy uncertainty on the effectiveness of monetary policy would be an interesting extension of our research. We leave this exercise for further study.

this paper applies the broad-based measure of financial uncertainty of Ludvigson et al. (2015), which extracts the variance of the unforecastable components from a large financial dataset, including variables from stock market portfolio returns, the bond market and commodity markets. Our paper contrasts with most existing studies of financial uncertainty which use the VIX index.<sup>6</sup> To the best of our knowledge, this is the first study that empirically and systematically investigates how a broad-based measure of financial uncertainty affects the impact of monetary policy shocks on financial and macroeconomic markets and assess all the possible explanations proposed in the literature.

This paper is closely related to Aastveit et al. (2017) and Pellegrino (2017). They employ non-linear interacted VARs to assess the real effect of monetary policy in the presence of economic uncertainty. They both find that economic activity is less sensitive to monetary policy shocks when economic uncertainty is high. Our work is different from theirs by focusing upon the role of financial uncertainty and additionally, the credit transmission channel, which has not been considered by the literature as far as we are aware.<sup>7</sup> Another relevant strand of literature studies the interaction of uncertainty and real activity through financial frictions and regimes (Christiano et al. (2014), Gilchrist et al. (2014), Caldara et al. (2016), and Alessandri and Mumtaz (2018)). For instance, Gilchrist et al. (2014) show that financial frictions are a powerful channel through which uncertainty affects investment, using a quantitative general equilibrium model. By estimating a nonlinear VAR where the economic uncertainty is proxied by the volatility of the structural shocks, Alessandri and

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<sup>6</sup>Bloom (2009) identifies financial uncertainty as the unconditional volatility of the stock market returns, proxied by the CBOE volatility index (VIX). However, as discussed in Jurado et al. (2015), this approach cannot distinguish between expected and unexpected movements. Moreover, the VIX index only extracts information from the stock market, instead of the entire finance industry.

<sup>7</sup>The non-linearity of interacted VAR which Aastveit et al. (2017) and Pellegrino (2017) explore is only reached for its second-order terms, whereas, our STVAR model achieve non-linearity by combining state-dependent models.

Mumtaz (2018) propose that uncertainty shocks could have different macroeconomic impacts depending on the corresponding financial states. All these studies shed light on the view that financial uncertainty could affect the transmission of economic uncertainty shocks via credit markets. Our paper is complementary to theirs, by focusing on the effectiveness of monetary policy stimulus conditional on different financial uncertainty levels.

By estimating the STVAR over the period 1960Q2 to 2017Q1, as expected, the results suggest that irrespective of the financial uncertainty states, a decrease in the federal funds rate has an expansionary impact on the economy and financial markets. Importantly, there is evidence of stronger but less persistent effects of monetary policy shocks during high financial uncertainty periods. This is different from the findings of Aastveit et al. (2017) and Pellegrino (2017), which suggest that monetary policy shocks are weaker during uncertain times, using the VIX index as the uncertainty indicator. Our results reconcile the conflicting explanations of the interest rate and credit monetary transmission channel between different financial uncertainty states. More specifically, the credit channel prevails in the short run so that a monetary expansion increases loans and asset prices greater during high financial uncertainty periods, causing a larger decrease of the cost of credit. This further leads to stronger responses of macroeconomic variables. Whereas in the long run, under heightened financial uncertainty, the interest rate channel dominates, in a way that real option effects, precautionary savings and the uncertainty-dependent price-setting mechanism make the monetary shocks less effective. Interest rate sensitive areas of the economy shall adopt a “wait and see” approach during periods of acute financial uncertainty, softening the impact of monetary policy.

The remainder of this chapter is organized as follows. Section 4.2 describes the widespread views of monetary transmission mechanisms based upon the



interest rate and credit channels. Section 4.3 lays out the empirical methodology of this work, with a discussion of the measure of financial uncertainty and the smooth transition VAR. Section 4.4 presents the data and Section 4.5 shows the main results on the effectiveness of monetary policy during high vs low financial uncertainty states. Section 4.6 conducts robustness checks and Section 4.7 concludes.

## **4.2 The Non-linear Monetary Transmission Mechanisms**

The main role of this section is to present the theoretical rationale of the ways in which financial uncertainty could affect the interest rate and credit channels within the monetary transmission mechanism.

### **4.2.1 The Interest Rate Channel**

Conventional monetary policy transmission mechanisms explore direct effects of monetary policy on the real and nominal economy. Take the interest rate channel as an example, it suggests that policy makers adjust the federal funds rate, to affect the cost of borrowing and raising capital, and consequently, household spending decisions on durable goods and firm investment. In the end, these changes influence the level of aggregate demand, final output and inflation.

To illustrate how the interest rate channel is associated with different states of uncertainty, this paper starts with the “real option” theory, which highlights the importance of fixed costs and partial irreversibility of investments (see, for example, Bernanke (1983), McDonald and Siegel (1986), and Dixit et al. (1994)

and Bloom (2009)). The idea is that the unknown future could make firms cautious about investing and prefer to wait and see how the future unfolds. This causes the real economy to become less responsive to changes in any policy stimulus. Therefore, countercyclical monetary policy needs to act more aggressively during periods of high uncertainty, to stabilize and stimulate the economy. Consumption can also be postponed due to high uncertainty, especially for durable goods such as housing and cars, which in turn, heightens precautionary savings. Even though lower interest rates lead to lower borrowing cost, people still tend to wait before undertaking an expensive move, whereas purchasing nondurables goods such as food is harder to delay.<sup>8</sup> In addition, firms' price setting behavior could also give uncertainty a role within the monetary transmission mechanism. This is associated with the fact that firms adjust prices more flexibly during periods of high uncertainty (Bachmann et al. (2013) and Vavra (2013)). This price flexibility leads monetary stimulus to mostly generate inflation rather than economic growth.<sup>9</sup>

To assess which among the theories of interest rate channel proposed in the literature are supported by our results, this paper includes measures of GDP, price, investment, unemployment rate, durable and nondurable consumption within the following empirical analysis.

#### **4.2.2 The Credit Channel**

In addition to the interest rate channel, several studies in the literature have argued that changes in financial conditions, especially the amount of credit

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<sup>8</sup>As surveyed by Bloom (2014), increasing risk premia could raise the cost of finance. The confidence effect of uncertainty makes agents act as if the worst outcomes would occur so they cut back hiring and investments. Precautionary saving reduces consumption and thus shrinks output in the short run.

<sup>9</sup>By setting up a micro-founded general equilibrium price setting model, Vavra (2013) argues that the estimated output responses to interest rate shocks can be weakened by up to 55% during times of high uncertainty relative to tranquil times.

firms and households have access to, may indirectly amplify monetary policy actions. This is the credit channel of the monetary-policy transmission (Bernanke and Gertler (1995), Zhensheng (2002), and Liu and Minford (2014)).

The credit channel is closely related to the external finance premium (EFP), which describes the difference between the cost to a firm raising funds externally via equity and debt and the cost of internal finance via retained earnings (Bernanke, 2007). The EFP inversely depends on the borrower's financial condition such as the net worth of the firm and the cost of credit. This creates a channel through which transitory economic shocks may have long-lasting effects, which is the so-called *financial accelerator*. Focusing on the principal-agent view of credit markets, Bernanke et al. (1996) and Kiyotaki and Moore (1997) rationalize the *financial accelerator* theoretically by uncovering that endogenous developments in credit markets tend to amplify shocks to the macroeconomy.<sup>10</sup>

Expansionary monetary policy is thought to decrease the size of the external finance premium, and through the credit channel, increase the amount of credit in the economy.<sup>11</sup> This can occur particularly through two conduits: the balance sheet channel and the bank lending channel. The balance sheet channel refers to the idea that changes in the interest rate impact the borrower's net worth, subsequently their balance or income statements. The bank lending channel, on the other hand, relates to the argument that changes in monetary policy may shift the supply of loans disbursed by commercial banks.

While the traditional view of the interaction between uncertainty and monetary policy effectiveness heavily relies on the irreversibility in the firm's decision through the interest rate channel (Bernanke (1983) and Bloom (2009)), the

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<sup>10</sup>Principal-agent problems in credit markets relate to the cost of borrowing and lending due to imperfect information and moral hazard problem between lenders (principals) and borrowers (agents).

<sup>11</sup>Gertler and Karadi (2015) argue that "modest" movements in interest rates promote "large" changes in credit costs, which are mostly due to the responses of both term premia and credit spreads.

more recent literature argues that financial frictions and uncertainty could play crucial roles in the transmission mechanism (Adrian and Shin (2009, 2010), Gilchrist et al. (2014), and Alessandri and Mumtaz (2018)). Especially, due to asymmetric information and moral hazard problem, a raise in financial uncertainty increases risk premia and external financial premium, further causing an increase in the cost of capital and a fall in the firm's net worth (Arellano et al. (2010), He and Krishnamurthy (2013), Christiano et al. (2014), and Gilchrist et al. (2014)). This implies that during periods of financial stress, firms are likely to suffer from liquidity constraints and seek external financing. Our work is motivated by the deliberation that, if expansionary monetary policy shocks affect the economy via financial markets, their impact might vary significantly depending on the fluctuations in asset prices and balance sheet conditions. Consequently, as indicated by Dahlhaus (2017), when financial uncertainty is high, for borrowers with low-net worth, changes in the net worth caused by monetary policy shocks may lead to large changes in the cost of credit, while this should not much affect the cost of credit for borrows in normal times with wide internal finance. We therefore expect stronger responses to monetary shocks through credit markets, when financial uncertainty heightens.

The theoretical literature has noted the existence of this nonlinear credit channel. For instance, Gertler and Gilchrist (1994) suggest that small firms are more responsive to expansionary monetary policy shocks the weaker the balance sheets of these firms. Bernanke et al. (1999) develop a dynamic general equilibrium model with the financial accelerator and uncover that firms that rely heavily on external credit markets respond more strongly to an interest rate drop, indicating that the impact of the financial accelerator is stronger when financial stress and uncertainty are high. More recent studies such as He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) focus on full equilibrium dynamics of an economy with instabilities and nonlinear

financial amplification effects. They uncover that when the financial market is under stress and financial constraints are binding, amplification is stronger, signalling the state dependence responses to shocks.

Furthermore, given these arguments, this work accounts for the variables relating to the credit channel: the external finance premium (EFP), the balance sheet channel and the bank lending channel in the study. This includes the spread between the Bank Prime Loan Rate and the 3-month T-Bill rate, the spread between the Baa and Aaa corporate bond yield, financial variables such as S&P 500 index and its volatility, and loan variables such as the bank credit and real estate loans. As the credit channel serves as an amplification effect besides the interest rate channel, small changes in monetary policy can have large effects on the economy and upon the financial sector if the credit channel theory holds.

## **4.3 Econometric Framework**

This section describes the econometric framework in this work. Specially, Section 4.3.1 presents the smooth transition vector autoregression model (STVAR) and Section 4.3.2 specifies the generalized impulse response functions (GIRFs).

### **4.3.1 Empirical Model**

A smooth transition vector autoregression (STVAR) model is estimated, in which the dynamics of macroeconomic variables  $X_t$  depend on the observable

transition variable  $z_{t-1}$ , and parameters  $\tau$  and  $c$ :<sup>12</sup>

$$\begin{aligned} X_t &= (1 - F(z_{t-1}; \tau, c))\Pi_L X_{t-1} + F(z_{t-1}; \tau, c)\Pi_H X_{t-1} + u_t, \\ u_t &\sim N(0, \Omega_t) \end{aligned} \quad (4.1)$$

The propagation of structural shocks is allowed to differ over states of financial uncertainty via the differences in lag polynomials between high  $\Pi_H$  and low  $\Pi_L$  financial uncertainty. The idiosyncratic component  $u_t$  is assumed to be normally distributed with variance  $\Omega_t$ . A STVAR model with state-dependent heteroskedasticity would be desirable, however, as claimed in Galvão and Owyang (2017), this specification could usually be achieved with  $c = 0$  and a calibrated  $\tau$ .<sup>13</sup> Therefore, the baseline analysis uses the STVAR model without state-dependent heteroskedasticity, as specified in Equation (4.1). The results of the STVAR model with state-dependent heteroskedasticity are further investigated in Section 4.6.3, in which the performed robustness checks are presented.

Note that the model in Equation (4.1) can be reparameterised for specification, estimation and evaluation are purposed as follows:

$$X_t = (B_1 + F(z_{t-1}; \tau, c)B_2)X_{t-1} + u_t \quad (4.2)$$

where  $B_1(L) = \Pi_L(L)$  and  $B_2(L) = \Pi_H(L) - \Pi_L(L)$ .

The model, therefore, implies that the economy is a combination of high financial uncertainty and low financial uncertainty dynamics, where  $F(z_{t-1}; \tau, c)$  is the transition function that determines the probability of being in each regime

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<sup>12</sup>Papers that have recently used STVAR in terms of uncertainty include Caggiano et al. (2014), Popp and Zhang (2016) and Caggiano et al. (2017b). Their studies focus on the effect of uncertainty shocks on the real activity during recessions and expansions. Unlike their research, this paper investigates the effects of monetary policy shocks conditional on the financial uncertainty.

<sup>13</sup>For instance, by employing a STVAR model with state-dependent heteroskedasticity, Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012) measure asymmetries over business cycles of the impact of fiscal policy shocks, while Caggiano et al. (2014) study the impact of uncertainty shocks on unemployment.

and  $z$  is the transition indicator. Particularly,  $z$  is dated  $t - 1$  to avert contemporaneous feedback.  $F(z_t; \tau, c)$  is presumed to be captured by a first-order logistic transition function:

$$F(z_t; \tau, c) = \{1 + \exp(-\tau(z_t - c))\}^{-1}, \tau > 0, z_t \sim N(0, 1) \quad (4.3)$$

The parameter  $\tau$  indicates the smoothness of the transition function  $F$ . As  $|\tau| \rightarrow \infty$ , the switches from one regime to another regime become sharper and the model is similar to a pure threshold model. If  $\tau = 0$ , the model collapses to a linear one. Therefore, this paper sets  $\tau > 0$  to keep the non-linearity feature. The threshold parameter  $c$  is a location parameter and controls the proportion of the sample in either state (high/low financial uncertainty). If the transition variable  $z_{t-1} < c$ ,  $F(z_t; \tau, c)$  gives more weight to the low financial uncertainty state ( $\Pi_L$ ).

The choice of transition indicator  $z_t$  is important in the estimation.  $z_t$  is set to be the financial uncertainty of Ludvigson et al. (2015). Using this financial uncertainty index has several advantages. First, it is derived from the variance of the unforecastable components of a broad-based factor model with nearly 200 financial variables. The popular financial conditions index (FCI) constructed by Hatzius et al. (2010), on the other hand, only pools information across 45 financial indicators and cannot reveal the uncertainty stemmed from the finance industrial. Second, the financial uncertainty index covers unanticipated shocks from different financial sectors such as equity, bond asset classes, and has a large span of history. Whereas, as mentioned above, alternative measures of financial uncertainty such as the VIX index are more narrowly defined. Third, the financial uncertainty is not the direct consequence of business cycle fluctuations or monetary policy.

Previous studies such as Caggiano et al. (2014) and Caggiano et al. (2017b) set  $z_t$  as the standardized moving-average of the GDP or industrial production

growth rate, and they consider the impact of uncertainty shocks on unemployment and monetary policy respectively in good and bad economic situations. However, as recessions can be caused by a range of reasons, such as tightening financial situations, oil shocks and political changes, it would be difficult to disentangle the role of uncertainty from recessions. A number of studies also suggest that business cycle fluctuations after 1980s are usually associated with financial stress, see for example, Stock and Watson (2012), Ng and Wright (2013) and Caldara et al. (2016). Therefore, different from the existing literature, this chapter conditions on financial uncertainty and measures how this influences the shocks of monetary policy on the macroeconomic and financial variables.

In comparison with Markov-Switching VAR (MSVAR) models, the advantage of the STVAR is that it allows for an observable transition variable driving the asymmetry transmissions. Given the previous findings in the theoretical and empirical literature, the STVAR fits in the economic motivation of this work: studying the effectiveness of monetary policy during different financial uncertainty states and revealing what drives the changes in two states. The MSVAR, on the other hand, ignores what induces regimes switches, therefore, the transition from one regime to the other could be abrupt.<sup>14</sup> This is inconsistent with the idea that the aggregate economy usually takes time to adjust and the transition from high financial stress to a low one is smooth.

We further conduct the Teräsvirta and Yang (2014a) test to detect non-linearity in the data. This test is suitable for the STVAR framework as it tests the null hypothesis of linearity vs a STVAR model with a single transition variable. In Appendix C.2, we provide more details about the implementation of non-linearity tests and find that the null hypothesis of linearity is strongly rejected at the

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<sup>14</sup>Hubrich and Tetlow (2015) measure the interaction of financial stress and the macroeconomy using a richly parameterized Markov-switching VAR. They argue that shocks transmission varies with stress states, which are defined as the periods of adverse latent Markov states.



significance level of 1%. This confirms the model specification of a nonlinear STVAR to estimate the financial uncertainty-dependent impulse responses to monetary policy shocks.

The estimation of STVAR is achieved using nonlinear least squares (NLS), presented in Appendix C.1. The optimal values of parameters  $c = 0.993$  and  $\tau = 8.487$  are obtained using the “grid search” algorithm, which controls the degree of asymmetry of the financial uncertainty and the speed of change from one state to the other respectively in the STVAR model. According to the optimal  $c$ , 81.9% of the sample period belongs to the low financial uncertainty state and 18.1% of it is included in the high financial uncertainty state.<sup>15</sup>

### 4.3.2 Generalized Impulse Response Function

Normally, standard impulse response functions (IRF) track the responses of real activities to impulses of monetary policy shocks conditional on a certain regime. In other words, the system is assumed to remain in a state with high financial uncertainty after the shock has hit the economy. While Auerbach and Gorodnichenko (2012) study the fiscal spending transmission during recessions and expansions using standard IRF, Owyang et al. (2013) argue that an expansionary shock is able to help the economy to recover from recessions. Specially, fiscal policy shocks which occur during recessions may drive the economy to a temporary expansion as a result of the “volatility effect”, as argued by Bloom (2009). Similarly, it is believed that monetary stimulus could ameliorate tight financial conditions and the omission of this possibility could bias the estimation of the impact of monetary stimulus in a standard VAR model. We, therefore, compute the generalized impulse response functions (GIRFs) à la Pesaran and Shin (1998), to consider both the endogenous

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<sup>15</sup>The percentage of recession of the sample period according to the NBER recession dates is 12.39%.

responses of uncertainty to a monetary policy shock and its feedback on the dynamics of the system. Another advantage of GIRFs is that it does not require orthogonalization of shocks and is invariant to the ordering of the variables in the STVAR. To estimate GIRFs in the STVAR framework, we assume that (i) a distinct set of histories at the impact (either high or low financial uncertainty state) (ii) that states can vary over horizon. Specially, GIRFs can be shown as:

$$\begin{aligned} GIRFs(h; \delta; \omega_{t-1}) = & E\{X_{t+h} \mid \tilde{\varepsilon}_t^{FFR} = \delta; \varepsilon_{t+h} = \tilde{\varepsilon}_{t+h}; \omega_{t-1}\} \\ & - E\{X_{t+h} \mid \varepsilon_{t+h} = \tilde{\varepsilon}_{t+h}; \omega_{t-1}\} \end{aligned} \quad (4.4)$$

where  $h$  is the horizon of impulse responses,  $\delta$  is the size of the shock from monetary policy,  $\omega_{t-1}$  is the history values extracted from the STVAR indicating a state in the sample and  $\tilde{\varepsilon}_{t+h}$  is a set of draws of residuals from the distribution  $\Omega_t$ . GIRFs enable the financial system to switch from one state to another state after a monetary stimulus, where the shock is calibrated to introduce a negative one-standard deviation impulse to the FFR in the model. Importantly, conditional on the estimated threshold parameter  $\hat{c}$  in Equation (4.1), a given history  $\omega_{t-1}$  can be classified as high or low financial uncertainty period. For each identified state, the GIRFs are computed using the following standard steps:<sup>16</sup>

1. Draw with replacement 500 histories belonging to each regime.
2. For each history, draw 500 different realizations of residuals.
3. Compute the median estimate across different residuals per each history.
4. Calculate median GIRFs across the 500 chosen histories.
5. Run 500 bootstrap replications for Equation (4.1).

The 68% confidence bands for GIRFs are computed by selecting the 16th and 84th percentiles over the distribution of the medians.

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<sup>16</sup>Pesaran and Shin (1998) provide detailed algorithms for calculating the GIRFs that are invariant to the ordering of the variables in the VAR.

## 4.4 Data

The dataset consists of US quarterly series over the period 1960:Q2 to 2017:Q1. The sample begins from 1960 as the financial uncertainty, which is the transition variable in the STVAR, is not available for earlier dates.<sup>17</sup> The description of other macroeconomics and financial variables in the nonlinear STVAR is presented in Table 4.1 and the data is transformed to be stationary.<sup>18</sup> The variables this paper considers consist of national accounts variables such as GDP and price (implicit price deflator); labor market variable such as the unemployment rate; investment, durable and non-durable consumption; financial variables such as the S&P 500 index and its volatility; spreads such as spread between the Bank Prime Loan Rate and the 3-month T-Bill, and spread between the Baa and Aaa corporate bond yield, loan variables such as bank credit and real estate loans.<sup>19</sup> All data series are transformed to be stationary. Concerning the lag order, two lags are used in the STVAR model and one lag in the transition variable, as suggested by the Hannan-Quinn criterion.<sup>20</sup> The federal funds' rate (FFR) is set to be the instrument of monetary policy. This is a common assumption to study the effect of monetary shocks in the empirical literature. Since the end of 2008, during the zero lower bound (ZLB) period, the "shadow rate" of Wu and Xia (2016) is employed instead of the FFR.<sup>21</sup> This shadow rate is close to the FFR before the ZLB period but could become negative during the ZLB period. Wu and Xia (2016) suggest that this rate could be used to capture unconventional monetary policy such as large-scale asset

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<sup>17</sup>Financial uncertainty data is available at <https://www.sydneyludvigson.com/data-and-appendixes/>.

<sup>18</sup>The transformation code and the source of the data can be found in Appendix C.1.

<sup>19</sup>The volatility of the S&P 500 index is calculated using the standard deviation of the daily S&P 500 within a quarter.

<sup>20</sup>Ivanov and Kilian (2005) suggest that Hannan-Quinn criterion seems to be the most accurate criterion for quarterly data. We also experimented higher orders and similar results are obtained.

<sup>21</sup>The Wu and Xia (2016) shadow rate is available at [https://www.frbatlanta.org/cqer/research/-shadow\\_rate.cfm](https://www.frbatlanta.org/cqer/research/-shadow_rate.cfm).

purchases (quantitative easing) when short-term interest rates become zero. This chapter further excludes the ZLB period in the robustness checks, to only focus on the effect of conventional on monetary shocks conditional financial uncertainty levels.

## 4.5 Empirical Results

Our results section begins by presenting the financial uncertainty series of Ludvigson et al. (2015) and the estimated probability in a high financial uncertainty state. Next, the financial uncertainty-dependent generalized impulse response functions (GIRFs) for various macroeconomic and financial variables are documented, based on the literature of monetary transmission mechanisms. Finally, the generalized forecast error variance decomposition (GFEVD) is obtained.

### 4.5.1 Financial Uncertainty

Figure 4.1 presents three uncertainty indicators: the VIX (Volatility Index) as in Bloom (2009), the financial uncertainty index of Ludvigson et al. (2015), which is the transition variable in the STVAR model, and the economic uncertainty of Jurado et al. (2015).<sup>22</sup> As is clear from Figure 4.1, these three uncertainty indicators have comovements but also have specific variations, as according to Table 4.2, the maximum correlation between them is 0.65. In particular, the VIX index, which measures the volatility of the stock market is more volatile than the broad-based financial and economic uncertainty indexes. Nevertheless, financial uncertainty is not simply equal to the volatility in the stock market and a proper uncertainty index requires excluding the

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<sup>22</sup> The optimal  $c$  is also plotted in Figure 4.1. Specially, if the value of financial uncertainty is above the estimated  $c$ , the corresponding periods enter the high financial uncertainty state.

forecastable components of the dataset. Furthermore, there are also differences between the broad-based financial and economic uncertainty indexes. Even though the peak of the financial uncertainty indicator occurred during the financial crisis in 2008 and financial uncertainty is on average higher in economic recessions, some spikes appeared during expansions, including the spikes occurred during the stock market crash at the end of 1987, the Asian crisis in 1997, the Enron scandal in 2001 and the Gulf War in 2003. This fact is essential to distinguish between the role played by financial uncertainty and economic recession for the results of impulse responses. In addition, it marks the contribution of this chapter, in comparison to Aastveit et al. (2017) and Pellegrino (2017) who study how economic uncertainty influences the effectiveness of monetary policy.

Figure 4.2 presents the transition function  $F(z_t)$ , which indicates the probability in a high financial uncertainty state. Since an increase in financial uncertainty corresponds to a deterioration in financial situations, a probability closer to one implies the prevalence of high financial stress state and it corresponds to the spikes of the financial uncertainty index in Figure 4.1. By contrast, a probability closer to zero corresponds to the low financial stress state.

#### **4.5.2 Asymmetric Effects of the Monetary Policy Shock**

This section presents the impulse responses of expansionary monetary policy shocks during high vs low financial uncertainty periods. As argued above in Section 4.3.2, we report the generalized impulse response functions (GIRFs) to take both the endogenous response of financial uncertainty to monetary policy shocks and its feedback on the dynamics of the STVAR model into account.

Following Pesaran and Shin (1998), instead of using the Cholesky decomposition with short-run restrictions to identify monetary policy shocks, we

generate GIRFs that are invariant to the ordering of the variables in the STVAR. Importantly, the vector of the endogenous variables in the STVAR model can be summarized as follows:

$$\begin{bmatrix} \text{Financial Uncertainty} \\ \text{GDP} \\ \text{Prices} \\ \text{Unemployment} \\ \text{Federal Funds Rate} \\ \text{Investment} \\ \text{Durable Consumption} \\ \text{Nondurable Consumption} \\ \text{Mprime-TB3MS} \\ \text{Baa-Aaa} \\ \text{S\&P 500} \\ \text{Volatility S\&P 500} \\ \text{Bank Credit} \\ \text{Real Estate Loans} \end{bmatrix} \quad (4.5)$$

where the descriptions of all the variables are presented in Table 4.1. These variables are common choices in the literature based on the interest rate and credit channel of the monetary transmission mechanisms.

Figures 4.3-4.4 show the responses of macroeconomic and financial variables by introducing a negative one-standard deviation impulse to the federal funds rate. Column 1 and 2 show the responses during high vs low financial uncertainty periods, respectively. Column 3 reports the results of differences between high uncertainty and low uncertainty states, to check whether the differences are significant. The shaded areas are the corresponding 68% confidence bands.

#### 4.5.2.1 Effects on Macroeconomic Variables

We first investigate the interest rate channel of a monetary policy shock and this usually relates to the reaction of macroeconomic variables after the policy implementation. Column 1 and 2 of Figure 4.3 show the impulse responses of macroeconomic variables during high and low financial uncertainty periods.

Strikingly, expansionary monetary policy shocks during periods of highly

uncertain have significantly larger but less persistent effects on macroeconomic variables compared to normal states. During periods of stress, although the STVAR system is allowed to endogenously switch from a state with high financial uncertainty to a state with low uncertainty after the shock happens, according to the GIRFs, financial uncertainty is not significantly affected by the monetary policy shocks. Whereas, expansionary policy shocks can significantly decrease financial uncertainty levels during tranquil times. This is consistent with the fact that, during the recent financial crisis despite the decreasing federal fund rate, financial uncertainty remained high. Importantly, in the state with high financial uncertainty, GDP significantly increases and reaches the maximum of nearly 1% after four quarters, however, the effect is not persistent. In the low financial uncertainty state, GDP significantly and consistently rises in response to a monetary expansion but only to the extent of around 0.4%. The difference between the state-dependent responses of GDP therefore is statistically significant positive at first but becomes negative after five quarters. Further, an expansionary monetary policy has positive and high but short-lived effects on prices for high uncertainty periods, which is consistent with the uncertainty-dependent price setting mechanism of Vavra (2013). During low financial uncertainty periods, however, prices decrease first following the expansionary monetary shock and increase to trend afterwards. The deflationary (inflationary) impact of an expansionary (contractionary) monetary policy shock in the early part of the responses has been identified by others and is known as the “price puzzle” (Bernanke and Blinder (1992), Hanson (2004), Giordani (2004), Christiano et al. (2005), and Castelnuovo and Surico (2010)). The existence of the price puzzle during low financial uncertainty periods is therefore common in the monetary VAR literature. Christiano et al. (2005) rationalize the price puzzle by presenting a model with nominal rigidities, which generates inertial inflation in response to a monetary policy shock.

Castelnuovo and Surico (2010) argue that the omission of variables capturing expected inflation in the VARs partially accounts for the price puzzle. While our findings suggest that Vavra's uncertainty-dependent price-setting mechanism dominates the effect of price puzzle during high financial uncertainty periods with a higher price level, the price puzzle still prevails when financial uncertainty is low.

Additionally, Figure 4.3 presents the impulse responses of unemployment (unemploy), CPI, I (investment), consumption on durable goods (Cdur) and on nondurable goods (Cnondur), providing more information about the effects of monetary policy shocks on macroeconomic variables. During low uncertainty periods, unemployment decreases significantly after a monetary stimulus and follows a reverse hump-shaped pattern before returning back to zero. The reaction of unemployment is much larger during high financial uncertainty periods, with the unemployment rate dropping by 1%. However, the effect does not last long. The response of CPI follows a similar pattern. Moreover, when the expansionary monetary policy shock hits the financial system with high uncertainty, this would induce an increase of investment of about 1.5% percentage points four quarters after the shock. Notwithstanding, this positive effect quickly becomes negative and is not persistent. Whereas, in low uncertainty periods, investment generally increases 0.5% and moves back to zero after 15 quarters. This reinforces the evidence that the effectiveness of monetary policy during high financial uncertainty periods is different from the one in the tranquil state.

As one explanation for the interest rate channel of monetary policy transmission is the existence of precautionary behaviour of households, especially for risk-averse consumers, total consumption is divided into consumption on durable goods and on nondurable goods. We find that durable consumption is more sensitive to monetary shocks than non-durable consumption, during



high uncertainty periods, echoing the risk-averse and the “wait and see” behaviour.

#### **4.5.2.2 Effects on Financial Variables**

To further understand where these differences in impulse responses stem from, we study the impact of monetary policy shocks on financial variables. The upper row of Figure 4.4 presents the state-dependent impulse responses of the external finance premium (EFP). The spread between the Bank Prime Loan Rate and the 3-month T-bill rate is used as the proxy for the EFP, following for example, Bernanke et al. (1999). This spread measures the premium that firms have to pay when they ask for credit externally in the banking system. The EFP quickly reaches its minimum around -2% after three quarters once the expansionary monetary shock takes place during high financial uncertainty times. This shock also has positive effects on the EFP during tranquil times. Although the cost of external funding reacts more in times of high uncertainty than in the normal state, the effect is temporary. Whereas, during low uncertainty periods, the impact of monetary shock on the EFP is persistent, which is confirmed by the “first negative later positive” difference between two states. To sum up, a monetary policy expansion decreases the cost of external funding more but quickly loses its effect during high financial uncertainty periods compared to times of low uncertainty.

The second row of Figure 4.4 shows the impulse responses of the spread between Baa and Aaa corporate bond (Baa-Aaa) to expansionary monetary shocks. Usually, the Baa-Aaa spread indicates whether the economy is in a period of financial stress. Especially, the yield spread between Baa and Aaa bonds widens during recessions, as investors switch to safer and higher-rated Aaa bonds, pushing down the yield. While in the normal state, the Baa-Aaa

spread increases slightly at the beginning and then decreases after five quarters. The responses of Baa-Aaa during time of financial stress is only significantly negative at the fourth quarter, with larger effects. Consequently, the cost of bond financing decreasing more but shortly stabilizes at the pre-shock level during times of high financial uncertainty due to the monetary expansion.

In addition, the middle rows of Figure 4.4 show the impulse responses of the S&P 500 and its volatility to expansionary monetary shocks. Stock market indices can be viewed as firms' wealth and net worth. During high financial periods, the S&P 500 significantly increases by 1%, then reverting to the pre-shock level after about six quarters. The response of the normal state reaches its maximum at around 0.5% after a year and then slowly goes back to zero. An opposite pattern arises for the state-dependent response of the volatility of stocks. To sum up, a monetary expansion during times of high financial uncertainty increases firms' worth and decreases the uncertainty with regard to the value of assets more, but this effect is short-lived compared to that in normal times.

We also present the effects of expansionary monetary policy shocks on the supply of credit, especially through commercial banks. Figure 4.4 shows the asymmetric impulse responses of bank credit and real estate loans for all commercial banks. Expansionary monetary policy increases the supply of loanable funds to banks and the amount of loans they make at different financial uncertainty levels. Nevertheless, this effect is larger but less persistent in a high financial uncertainty state.

### **4.5.3 Forecast Error Variance Decomposition**

After studying the impulse responses of macroeconomic and financial variables to monetary shocks, we assess the contribution of monetary shocks on

the dynamics of variables during high vs low financial uncertainty periods. Following Lanne and Nyberg (2016), the generalized forecast error variance decomposition (GFEVD) is measured based on the generalized impulse response function (GIRF). This study is the first one that conducts financial-uncertainty dependent GFEVD of monetary shocks. This new GFEVD is not restricted to linear VAR and is implemented as follows:

$$\lambda_{ij,\omega_{t-1}}(h) = \frac{\sum_{l=0}^h GIRF(h; \delta_{jt}; \omega_{t-1})_i^2}{\sum_{j=1}^p \sum_{l=0}^h GIRF(h; \delta_{jt}; \omega_{t-1})_i^2}, \quad i, j = 1, \dots, p \quad (4.6)$$

where  $j$  and  $i$  denote the specific shock and variable,  $h$  is the horizon and  $\omega_{t-1}$  refers to the history. Therefore, the denominator in Equation (4.6) represents the cumulative effect of all the shocks, whereas the numerator is the effect of the  $j$ th shock over  $h$  periods.

Table 4.3 documents the outcomes of the uncertainty-dependent 4, 8, 12 and 16 quarter-ahead forecast error variance decomposition analysis. We report the estimated contribution of monetary policy shocks and compare their different impacts for various horizons. Conditional on the STVAR and looking at the initial stage (4 quarter-ahead), monetary policy shocks seem to explain a substantial share of the variance of the external finance premium (EFP) and the Baa and Aaa bond yield spread during high financial uncertainty periods. This is reasonable as the ability that firms could borrow externally is directly linked to interest rate changes, especially during times of financial stress. During low financial uncertainty periods, however, monetary policy shocks turn out to be less powerful one year after implementation. Quite differently, starting from 8 quarter-ahead, monetary policy shocks are estimated to have a milder contribution to the forecast error variances when financial uncertainty is high, and for 12 and 16 quarter-ahead, monetary policy shocks apparently play more important roles during the low financial uncertainty state. These findings suggest that in the short run, monetary stimulus can explain a larger proportion of

the variance for the variables we consider when financial uncertainty is high, whereas, in the long run, contribution of policy shocks becomes stronger during low financial uncertainty periods. This is in line with the results from the impulse response function analysis that monetary policy shocks have larger but less persistent effect on macroeconomic and financial variables during high financial uncertainty periods.

#### **4.5.4 Discussion**

The findings of our impulse response and forecast error variance decomposition analysis have several important implications. First, GDP, prices, investment and durable consumption tend to increase and the unemployment rate decreases after an expansionary monetary policy, pointing to the conventional interest rate channel of monetary policy on macroeconomic variables. Additionally, in the short run, the decrease of the credit risk spreads, such as the EFP and Baa and Aaa spread, and the increase of S&P 500 index, provide evidence for the existence of the credit channel of monetary policy transmission. We further break down the credit channel into the balance sheet channel and the bank-leading channel. The positive response of S&P 500, which represents the entrepreneurs' wealth in both high and low financial uncertainty regime backs the potential balance sheet channel. Besides, a monetary policy expansion also impacts the EFP by increasing the amount of intermediated credit-particularly, loans issued by commercial banks. This corresponds to the positive responses of bank credit and real estate loans in both financial uncertainty states.

Second and more importantly, we uncover that in general, expansionary monetary policy shocks have different effects for different financial uncertainty conditions. Notably, macroeconomic and financial variables are affected more in the case of high financial uncertainty, though this effect diminishes quite

quickly. As a consequence, standard linear VAR seems to capture the average effects of expansionary monetary shock. A nonlinear framework that distinguishes the dynamics in different financial states, such as the STVAR model we apply in the chapter, is more realistic and appropriate. In Appendix Figure C.1 to C.2, we further present the impulse response results when the VIX index and the economic uncertainty in Jurado et al. (2015) are used as the uncertainty indicator in the STVAR model. We uncover that expansionary monetary policy shocks are less effective during periods of elevated uncertainty, consistent with the findings in Aastveit et al. (2017) and Pellegrino (2017). This further indicates that the broad-based financial uncertainty index we employ in this paper has different impact on the effectiveness of monetary policy shocks compared to alternative uncertainty indicators. In particular, the VIX index which is widely used as a financial uncertainty index in the previous literature, cannot capture all the fluctuations in the financial market, therefore, may undermine the nonlinearities in the credit channel of monetary policy transmission.

Our results reconcile the seemingly contradictory conclusions reached in Hubrich and Tetlow (2015) that monetary policy is weaker during episodes of high financial stress and in Dahlhaus (2017) that an expansionary monetary shock has stronger and more persistent effects when the financial condition deteriorates. We suggest that even though during high financial uncertainty periods, macroeconomic and financial variables react more strongly to monetary policy shocks than during normal times, but this effect is less persistent. Consequently, expansionary monetary policy is more effective on the economy and financial market in the very short run but less effective in the long run during times of high financial uncertainty. These differences seem to link with the nonlinearities in the interest rate and credit monetary transmission channels. Particularly, in the short run, the credit channel dominates, which causes stronger decrease in the EFP during high financial uncertainty periods. This

consecutively heightens responses of macroeconomic variables. In the long run, on the other hand, the explanations relating to interest rate channel, such as the theory of real option, precautionary savings and uncertainty-dependent price setting mechanisms play important roles, making monetary stimulus less effective during times of high financial uncertainty.

From a policy point of view, our results also shed light on how to implement monetary policies during different financial uncertainty states. While regarding economic uncertainty, Bloom (2014) suggests that policies aiming to stimulate the economy should be more aggressive during recessions. Moreover, Baker et al. (2016) propose that policies that are opaque or hyperactive seem to raise uncertainty vice versa. Our evidence on the financial uncertainty-dependent effectiveness of monetary policy extends the literature by arguing that policymakers should implement different policies during different financial uncertainty states. Notably, expansionary monetary policy has shorter-lived effect on tackling economic and financial issues during periods of high financial uncertainty. Fiscal stimulus and improved financial prudential policies are necessary to prompt economic growth and stabilize the financial market.

## **4.6 Robustness Checks**

In this section, we check the robustness of our baseline results. We first exclude the zero lower bound (ZLB) periods. Besides, we consider potentially relevant omitted variables from a large macroeconomic and financial dataset. Finally, a STVAR model with state-dependent variances is applied.

### 4.6.1 Excluding the Zero Lower Bound (ZLB) Periods

From December 2008, to December 2015, the effective federal funds rate was in the 0 to 0.25% percent range targeted by the Federal Open Market Committee, the so-called “zero lower bound” environment. In the mean time, central banks implemented quantitative easing (QE), also known as the large-scale asset purchases to stimulate the economy. This unconventional monetary policy can affect government bond yields through the signalling and portfolio balance channels of quantitative easing, see for example, Christensen and Rudebusch (2012) and Bauer and Neely (2014). The signalling channel reflects the lower expectations of short-run interest rates after the asset purchase announcements. On the other hand, the portfolio balance channel implies that QE can reduce term premiums in both long-term yields and their substitutes. Especially, the portfolio balance transmission channel could be more effective during high financial uncertainty periods, when the financial situation deteriorates and the credit spread heightens.

We take zero lower bound environments into account by employing the Wu and Xia (2016) shadow rate as a proxy for unconventional monetary policies. Nevertheless, a number of papers in the literature have suggested that higher uncertainty has more negative effects if monetary policy can no longer perform its usual stabilizing function during ZLB (see for example, Basu and Bundick (2017) and Caggiano et al. (2017a)). The model is then estimated during the sample period 1960:Q2 to 2008Q3, excluding the times of the financial crisis affected by the ZLB.<sup>23</sup>

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<sup>23</sup>It would be interesting to study the zero lower bound (ZLB) period alone, but there will not be enough data to run the STVAR model.

### 4.6.2 FAVAR

Even though we already accommodate possible economic and financial variables in the STVAR model, the baseline results may be spurious and distorted if the VAR model does not embed sufficient information to estimate monetary policy shocks. In light of the FAVAR model of Bernanke et al. (2005), we tackle this potential omitted variable issue by adding one factor extracted from the McCracken and Ng (2016) large dataset using the principle component analysis. This dataset consists of 135 series across economic and financial areas.

### 4.6.3 STVAR with State-dependent Variances

In the baseline analysis, we allow for differences in the propagation of monetary shocks through the differences in lag polynomials  $\Pi_L$  and  $\Pi_H$  in Equation (4.1). In this section, another way for differences in the transmission of shock is allowed via the contemporaneous differences in the covariance of shocks  $\Omega_L$  and  $\Omega_H$ . Especially, the variance of the disturbance term  $\Omega_t$  of Equation (4.1) can be written as:

$$\Omega_t = (1 - F(z_{t-1}; \tau, c))\Omega_L + F(z_{t-1}; \tau, c)\Omega_H \quad (4.7)$$

The transition function changes to:

$$F(z_t) = \frac{\exp(-\tau z_t)}{1 + \exp(-\tau z_t)} \quad (4.8)$$

The smoothness parameter  $\tau$  is calibrated to have the same duration of high financial uncertainty periods according to the STVAR model we built on in our baseline analysis. Therefore we assume that 18.1% of the sample period consists of periods of elevated financial uncertainty. This means that  $\tau$  is calibrated so that  $\Pr(F_z \geq 0.819) \approx 0.181$ , thus,  $\tau = 1.84$ .



Figure 4.5 to 4.6 report the impulse response results in high vs low financial uncertainty periods of both robustness checks. The results coming from the robustness checks are quantitatively similar and are comparable to the baseline model. Admittedly, some differences between different specifications are presented. The STVAR excluding ZLB periods and the one with FAVAR predict a somewhat milder response of macroeconomic and financial variables. This may indicate the existence of the portfolio balance channel of the unconventional monetary policy and the importance of taking the omitted variable issue into account. Nevertheless, all scenarios confirm the increase of GDP, prices, investment, consumption, EFP and loans in response to an expansionary monetary shock. Importantly, nonlinearities of impulse response functions are also supported by the robustness checks. While some heterogeneity exists across different scenarios, all cases indicate a larger but short-lived responses during periods of elevated financial uncertainty. By contrast, under low financial stress, macroeconomic and financial variables tend to react in a smaller but longer extent.

## 4.7 Conclusion

The recent financial crisis has strengthened interest in the interactions between financial uncertainty shocks and the macroeconomy. Importantly, the literature has suggested that financial uncertainty, in contrast to economic uncertainty, is of great importance for business cycle fluctuations both as an origin and as a propagating mechanism. However, little work has been done on answering the effects of financial uncertainty as a conditional variable on other structural shocks, particularly on monetary policy shocks.

In this paper, a smooth transition vector autoregression (STVAR) is applied to distinguish the effect of high and low financial uncertainty on monetary

stimulus. The transition variable we use in this study is financial uncertainty, which is from Ludvigson et al. (2015). This uncertainty measure extracts the variance of the unforecastable components from a large financial dataset. Unlike the VIX index suggested by Bloom (2009), this financial uncertainty index distinguishes between expected and unexpected movements in the financial market. Also the VIX index which only focuses on the fluctuations in the stock market, is more narrowly defined than the financial uncertainty measure used in this chapter.

Our analysis provides evidence that the transmission of monetary expansion is different between high and low financial uncertainty periods. More specifically, we find that monetary policy shocks have stronger but shorter-lived effects on macroeconomic and financial variables, such as output, consumption, investment and the external finance premium (EFP), during episodes of high financial uncertainty compared to tranquil periods. This is different from the findings of Aastveit et al. (2017) and Pellegrino (2017). They suggest that monetary policy shocks affect the economy to a lesser extent when uncertainty is high, using the VIX index and the economic uncertainty in Jurado et al. (2015) as uncertainty indicators. The uncertainty-dependent responses we find seem to stem from nonlinearities in the interest rate and credit channel. That is, in the short run, during periods of financial stress, firms are likely to seek external financing. Therefore, loans and asset prices are more sensitive to cost of credit changes during financial fluctuations than normal periods. This causes larger decrease in the EFP, which in turn, promotes stronger responses of real economy variables. In the long run, however, partial irreversibility of investment, precautionary savings and uncertainty-dependent price-setting mechanism effects dominate, making monetary policy less effective when financial uncertainty is high.

TABLE 4.1: Data Description

No.	Name	Abbreviations	Description
1	GDP	GDP	Real Gross Domestic Product
2	Prices	Prices	Gross Domestic Product: Implicit Price Deflator
3	Unemployment Rate	Unemploy	Civilian Unemployment Rate
4	investment	I	Real Gross Private Domestic Investment
5	C_durable	Cdur	Personal consumption expenditures: Durable goods
6	C_nondurable	Cnondur	Personal consumption expenditures: Nondurable goods
7	Mprime-TB3MS	EFP	Bank Prime Loan Rate and 3-Month Treasury Bill Spread
8	BAA-AAA	Baa-Aaa	Moody's Seasoned Baa and Aaa Corporate Bond Yield Spread
9	S&P 500	S&P 500	S&P 500 COMPOSITE - PRICE INDEX
10	Volatility S&P	Vol S&P 500	Volatility of S&P 500 COMPOSITE - PRICE INDEX
11	LOANINV	Tloans	Bank Credit at All Commercial Banks
12	REALLN	Rloans	Real Estate Loans, All Commercial Banks

*Notes:* This table presents the data description of the variables we include in the STVAR model. The data set is at quarterly frequency, with 228 observations.

TABLE 4.2: Correlation Between Different Uncertainty Indicators

	VIX	Economic Uncertainty	Financial Uncertainty
VIX	1		
Economic Uncertainty	0.45	1	
Financial Uncertainty	0.65	0.57	1

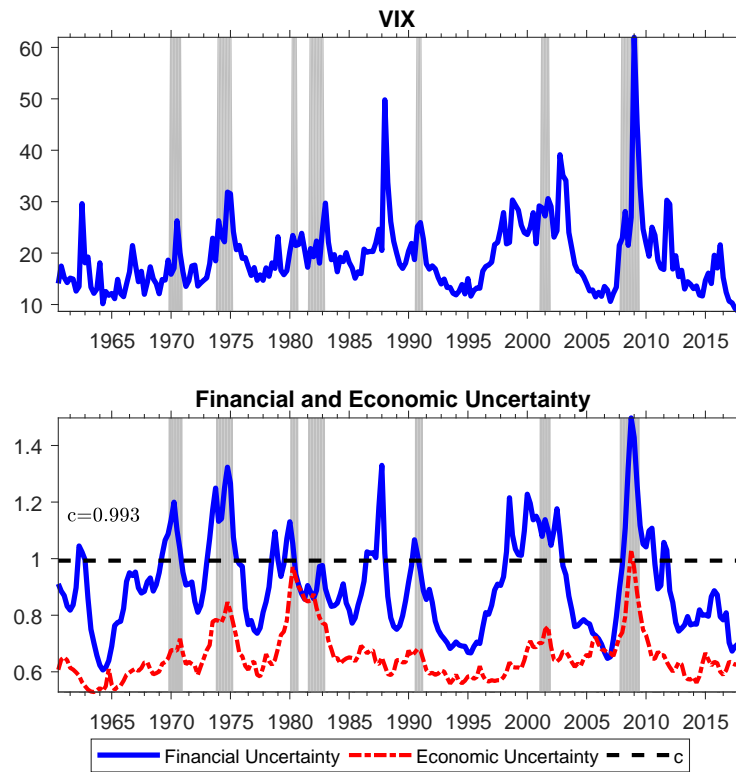
*Notes:* This table shows the correlation between three uncertainty indicators: the VIX (Volatility Index) as in Bloom (2009), the financial uncertainty of Ludvigson et al. (2015) we base on and the economic uncertainty of Jurado et al. (2015).

TABLE 4.3: Role of Monetary Policy Shocks, 4, 8, 12 and 16 State-dependent Quarter-ahead Forecast Error Variance Decomposition

		<i>4 quarter-ahead</i>							
		GDP	Prices	I	Cdur	EFP	Baa-Aaa	S&P 500	TLOAN
High Uncertainty		2.06	2.00	2.87	2.79	4.28	5.23	2.94	2.80
Low Uncertainty		1.60	1.26	1.54	0.76	2.19	1.64	1.41	1.17
		<i>8 quarter-ahead</i>							
		GDP	Prices	I	Cdur	EFP	Baa-Aaa	S&P 500	TLOAN
High Uncertainty		3.00	2.75	2.90	3.05	4.03	4.32	2.63	2.96
Low Uncertainty		3.11	1.97	3.14	2.14	2.84	2.05	2.14	1.70
		<i>12 quarter-ahead</i>							
		GDP	Prices	I	Cdur	EFP	Baa-Aaa	S&P 500	TLOAN
High Uncertainty		3.58	3.11	3.29	3.34	4.19	3.98	3.06	3.43
Low Uncertainty		4.27	3.99	4.51	3.55	5.70	4.33	3.74	3.72
		<i>16 quarter-ahead</i>							
		GDP	Prices	I	Cdur	EFP	Baa-Aaa	S&P 500	TLOAN
High Uncertainty		3.89	3.38	3.40	3.62	4.38	3.95	3.41	3.72
Low Uncertainty		5.02	4.15	5.27	4.62	5.88	4.47	5.03	3.95

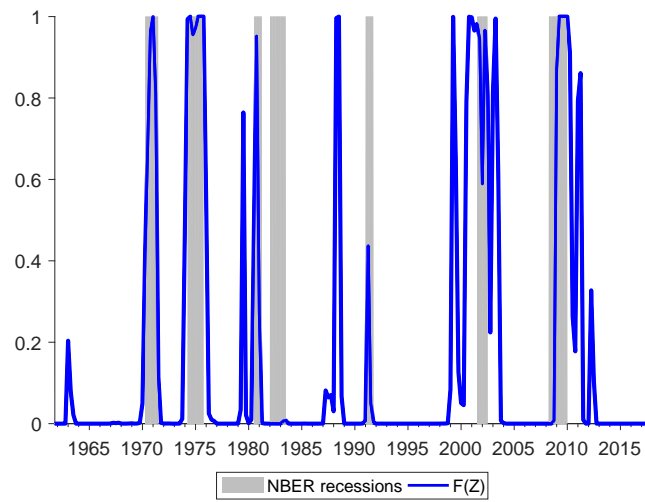
*Notes:* This table presents the results of the 4, 8, 12 and 16 quarter-ahead state-dependent forecast error variance decomposition of the expansionary monetary policy shocks. Due to lack of space, only the results for some representative variables are showed, including GDP, Prices, investment (I), durable consumption (Cdur), external finance premium (EFP), Baa and Aaa corporate bond yield spread (Baa-Aaa), S&P 500 price index (S&P 500) and bank credit at all commercial banks (Tloans). The results of other variables are quantitatively similar.

FIGURE 4.1: Uncertainty Indicators



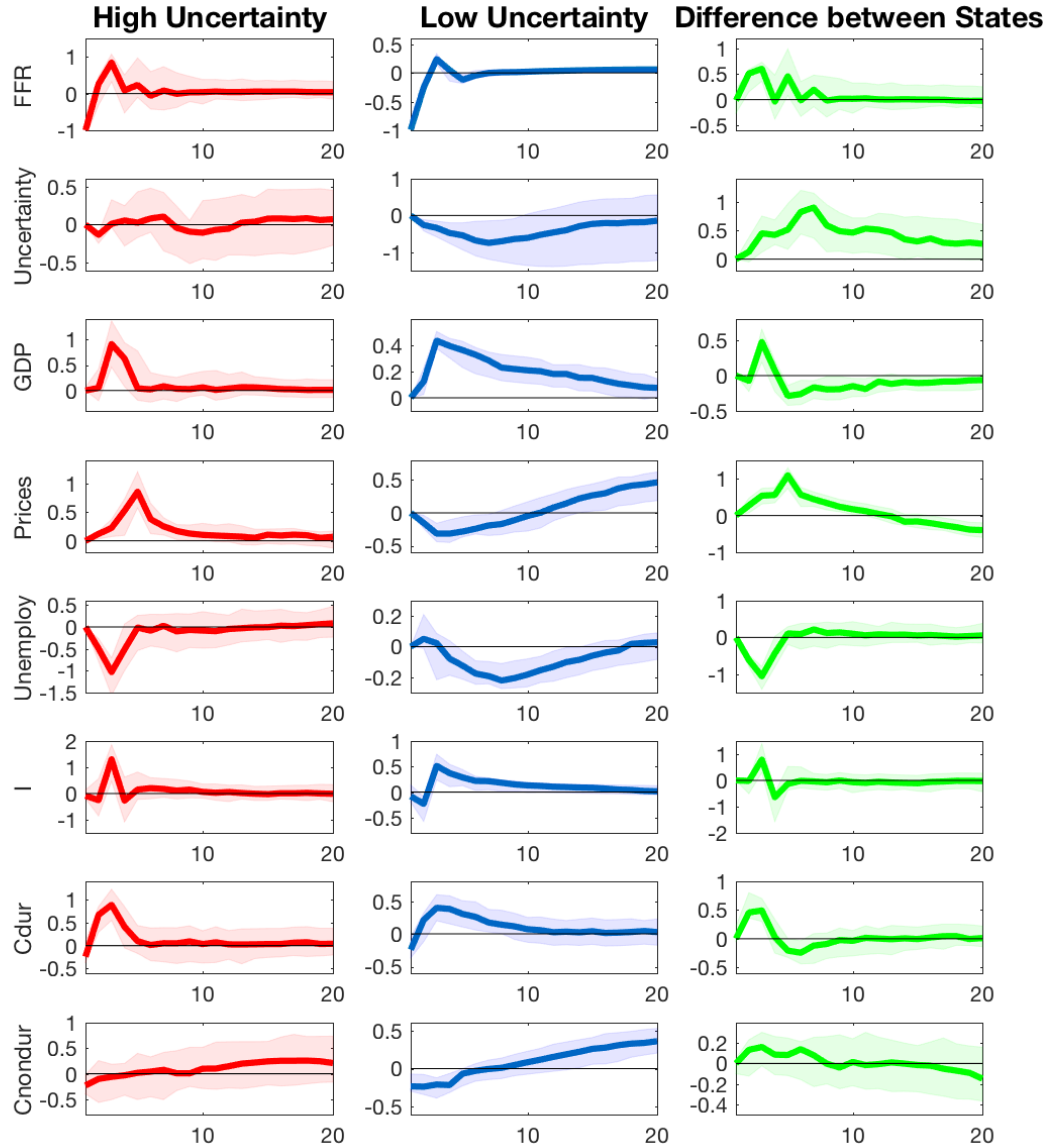
*Notes:* The graph plots three uncertainty indicators: the VIX (Volatility Index) as in Bloom (2009), the financial uncertainty of Ludvigson et al. (2015) we base on and the economic uncertainty of Jurado et al. (2015). The NBER recessionary dates are represented by the grey bars. The horizontal dashed line is the optimal value  $c$ , which controls the proportion of the sample in low or high financial uncertainty state.

FIGURE 4.2: Probability of Being in a High Financial Uncertainty State



*Notes:* This figure plots the probability of being in a high financial uncertainty state, which is the transition function  $F(z_t)$  in our case. The shaded areas correspond to the NBER recession dates.

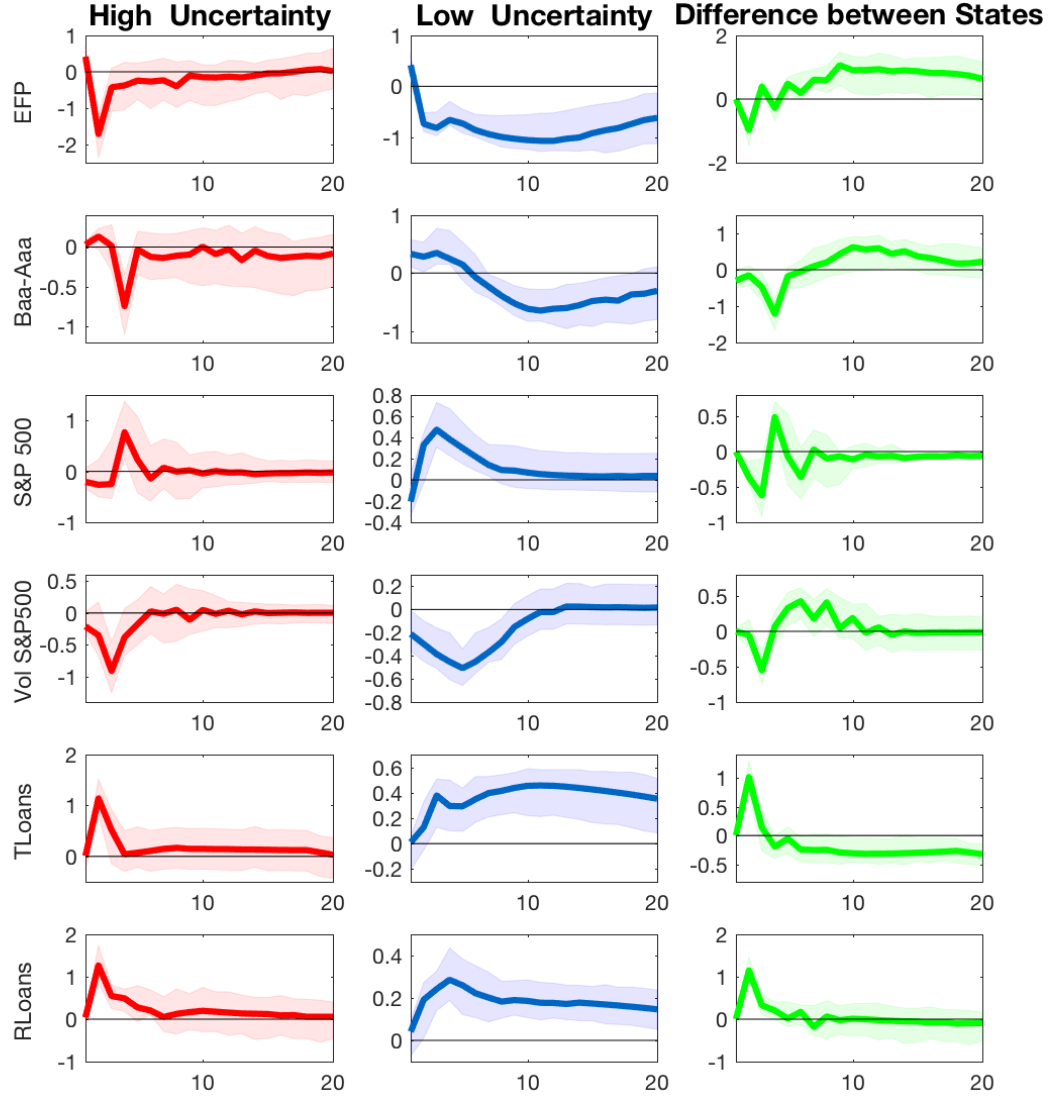
FIGURE 4.3: State-dependent Responses of Macroeconomic Variables, to a Expansionary Monetary Policy Shock.



*Notes:* The shock is one percentage unexpected decrease in FFR. The first column shows the response in the high financial uncertainty periods, the second and the third column present the differences between high uncertainty and low uncertainty states respectively. The description of the variables is as follows: FFR is the federal funds rate; Uncertainty is the financial uncertainty in Ludvigson et al. (2015) and GDP is the real GDP; Prices are the implicit price deflator of GDP; Unemploy is the unemployment rate; CPI is the Consumer Price Index; I is the investment; Cdur is the durable consumption and Cnondur is the nondurable consumption. The sample period is from 1960Q2 to 2017Q1 and we also present the 68% bootstrapped confidence bands.

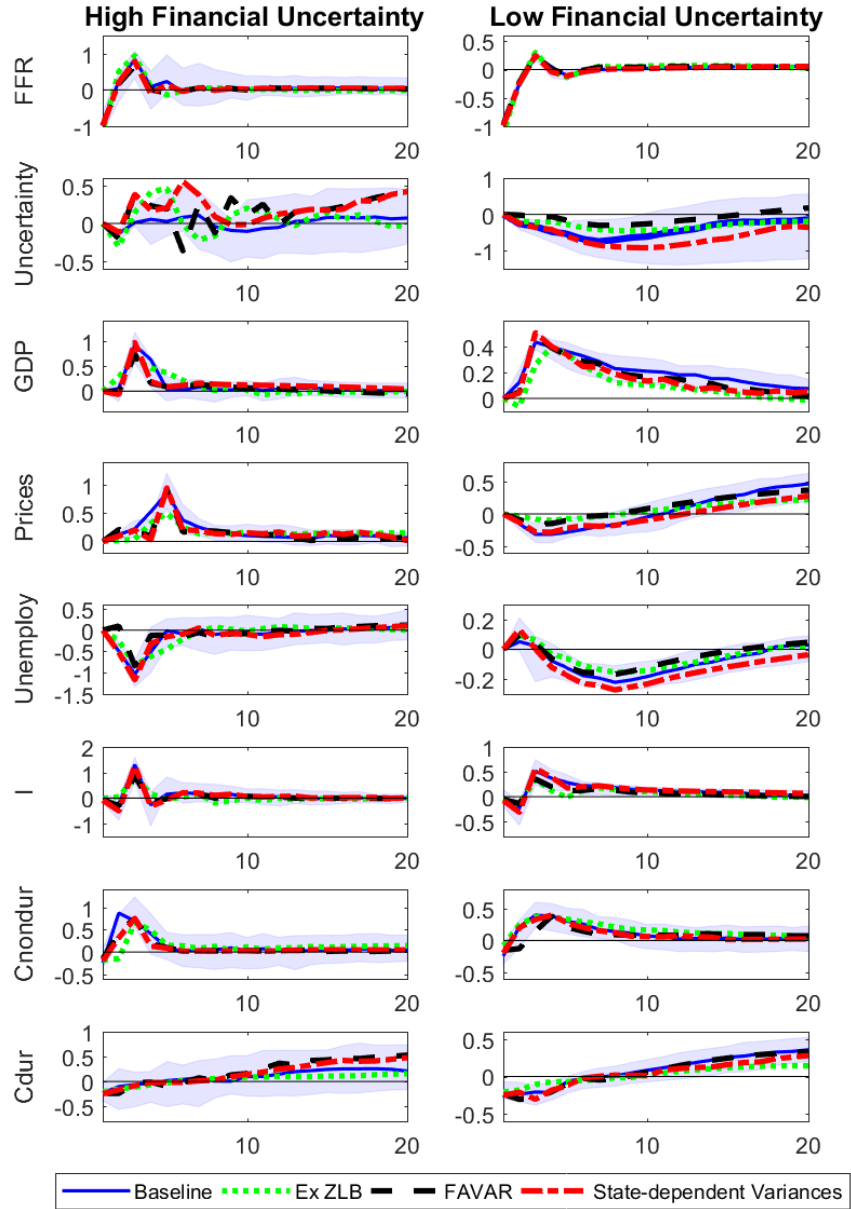


FIGURE 4.4: State-dependent Responses of Financial Variables, to a Expansionary Monetary Policy Shock.



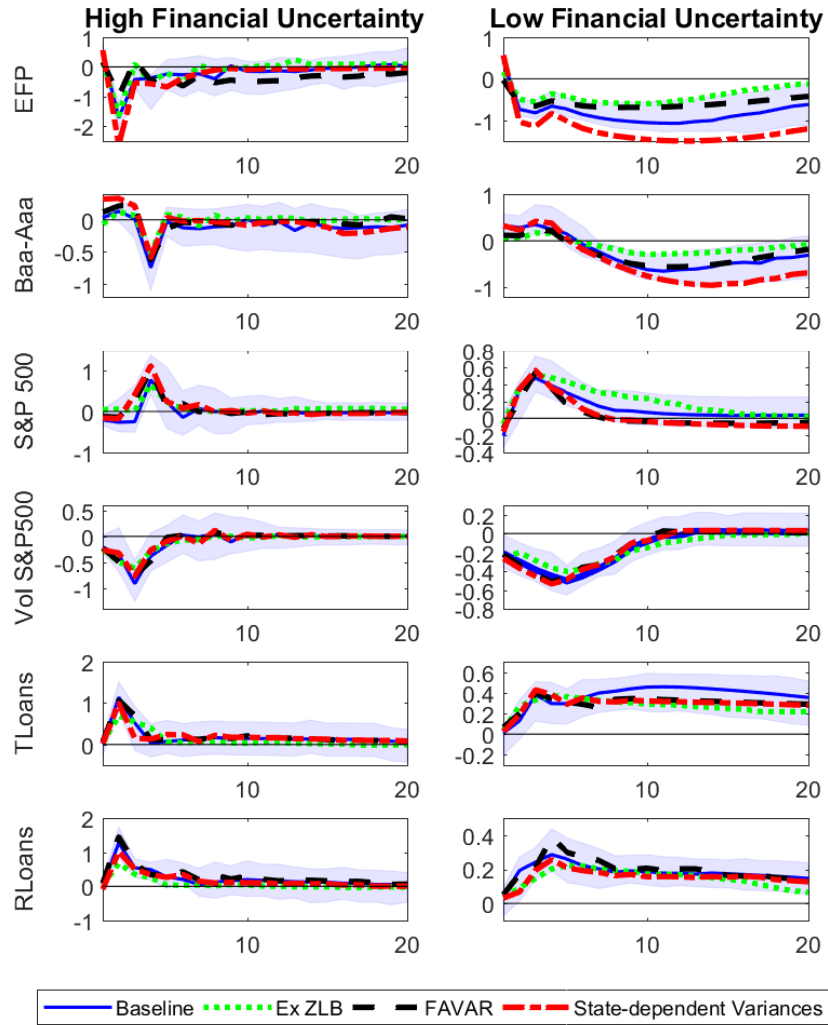
*Notes:* The shock is one percentage unexpected decrease in FFR. The first column shows the response in the high financial uncertainty periods, the second and the third column present the differences between high uncertainty and low uncertainty states respectively. The description of the variables is as follows: EFP is the external finance premium, presented by the bank prime loan rate and 3-month treasury bill spread; Baa-Aaa is the Baa and Aaa corporate bond yield spread; S&P 500 is the S&P 500 composite price index; Vol S&P 500 is the volatility of the S&P 500 index; TLoans is the bank credit and RLoans is the real estate loans. The sample period is from 1960Q2 to 2017Q1 and we also present the 68% bootstrapped confidence bands.

FIGURE 4.5: Robustness Checks: State-dependent Responses of Macroeconomic Variables to a Expansionary Monetary Policy Shock.



*Notes:* The shock is one percentage unexpected decrease in FFR. The first column shows the response during high financial uncertainty periods, the second presents the results during low uncertainty periods. Baseline: baseline smooth transition VAR; Ex ZLB: estimating excluding ZLB periods; FAVAR: VAR with a common factor extracted from a large financial dataset; State-dependent Variances: smooth transition VAR with state-dependent variance following Auerbach and Gorodnichenko (2012). The detailed description of macroeconomic variables can be found in Table 4.3. The sample period is from 1960Q2 to 2017Q1 and we also present the 68% bootstrapped confidence bands.

FIGURE 4.6: Robustness Checks: State-dependent Responses of Financial Variables to a Expansionary Monetary Policy Shock.



*Notes:* The shock is one percentage unexpected decrease in FFR. The first column shows the response during high financial uncertainty periods, the second presents the results during low uncertainty periods. Baseline: baseline smooth transition VAR; Ex ZLB: estimating excluding ZLB periods; FAVAR: VAR with a common factor extracted from a large financial dataset; State-dependent Variances: smooth transition VAR with state-dependent variance following Auerbach and Gorodnichenko (2012). The detailed description of macroeconomic variables can be found in Table 4.4. The sample period is from 1960Q2 to 2017Q1 and we also present the 68% bootstrapped confidence bands.

## Chapter 5

# Conclusion

This thesis focuses on how financial markets interact with the overall economy. We study the predictability of stock returns and relate it to the business cycle. We further explore global financial integration, especially the links between international stock markets. Finally, we analyze the effectiveness of monetary policy under different financial conditions.

Chapter 2 starts with the core area of financial economics, which can trace back to Dow (1920): stock return predictability. The literature has pointed out that parameter instability and model uncertainty are the two broad challenges for stock return predictability. Indeed, Welch and Goyal (2008) argue in a comprehensive paper that commonly used asset price predictors perform poorly both in-sample and out-of-sample. Moreover, the forecast performance of the ordinary least squares (OLS) regression is unstable and only improves for some predictors in specific periods of stress. Even though, the exact degree of time-variation in coefficients and in forecasting models has not been explored.

Chapter 2, therefore, constructs the dynamic mixture model averaging (DMMA) method, which takes possible degrees of time-variation in coefficients and in forecasting models into account. This implies that DMMA accommodates fast, slow or even constant changing coefficients and forecasting models, fitting in

the stock market where investors flexibly adjust risk-aversion and their beliefs on the importance of the predictors. Especially, using dynamic linear models, DMMA nests combination methods such as the dynamic model averaging (DMA) in Raftery et al. (2010), commonly used Bayesian model averaging (BMA) and equal model weights.

The empirical results in Chapter 2 show that our DMMA method generates more accurate forecasts compared to the historical mean (HM) benchmark across different sample periods, statistically and economically. Moreover, DMMA outperforms its nested model combination methods including BMA, DMA and equal-weighted models in terms of point accuracy. The results further confirm the importance of time-varying coefficients in the predictive regressions. By tracing the sources of uncertainty, this chapter analyzes the origins of the forecast improvements and uncovers that DMMA adapts the pattern in the unstable stock market and precisely identifies the time variation in coefficients and the combination method, leading to mitigation of estimation risk.

In addition, Chapter 2 links DMMA's predictability with the business cycle. While DMMA still slightly outperforms the benchmark HM model during expansions, DMMA's superior performance is mainly driven by recessions. Interestingly, simple models with constant coefficients and equal weights tend to perform well in expansions. This may suggest that complex model such as DMMA quickly captures changes in time of stress, while simple models which are static become advantageous during expansions.

After focusing on behaviour of a single stock market, Chapter 3 investigates the extent and ways in which international financial markets are closely linked together. We do so by constructing a novel financial integration measure. In general, financial integration is measured as the proportion of the variance of an economy's stock return explained by the global component in a factor

model. If an economy is fully integrated, then financial integration measure should be close to one. However, a common assumption of this framework is that both the linkage between global factors and individual stock return and the volatility are constant. Chapter 3 therefore measures financial integration by capturing the changes in the economy in a way that time-variation in factor loadings and stochastic volatility are allowed in the factor model. Specifically, the global factors are extracted from the stock markets using out-of-sample principal components, following Pukthuanthong and Roll (2009). By investigating the features of financial integration, Chapter 3 uncovers that even though financial integration presents a generally upward trend for the advanced economies, there still exists country-specific effects and none of the economies reach full financial integration consistently. Among the economies this chapter considers, Hong Kong has the highest financial integration, Japan has the lowest and the United States, as the largest economy in the world, also presents greater integration compared to other countries. Importantly, by conducting statistical tests and comparing with the factor model with constant loadings and risk, Chapter 3 suggests that incorporating time-varying factor loadings and stochastic volatility matters for the measurement of financial integration.

Chapter 3 further identifies what leads to this increasing financial integration by decomposing it into risk due to global factors, country effect and estimation error. In most cases, increasing global risk instead of decreasing country effect is the key element that drives integration. To understand what drives financial integration economically, Chapter 3 provides initial evidence about the predictability of financial integration based upon macroeconomic fundamentals, including international trade, investment openness, growth in real per capital GDP, the NBER recession dummy and most importantly the VIX index. This exercise has important implications for investors with respect to

portfolio diversification, as well as policy makers in terms of monitoring contagion risk and smoothly implementing domestic policies, see for discussions in Driessen and Laeven (2007), Kose et al. (2009), and Blanchard et al. (2010). The results show that financial integration is highly predictable by combining dynamic linear models using the dynamic model averaging proposed by Raftery et al. (2010) and Koop and Korobilis (2012). Importantly, besides international trade, we uncover that the VIX index, as an indicator of uncertainty, is informative about the movements of financial uncertainty across different countries. This reflects the vulnerability of financial markets to uncertainty and provides insights for peripheral countries to introduce self-insurance policies to protect themselves from the global movements.

Chapter 4 further studies how financial uncertainty affects the impact of structural shocks on the economy, especially monetary policy shocks. Financial uncertainty has been a popular topics since the financial crisis for both researcher and policy makers. The recent literature has suggested that financial uncertainty is a crucial source of business cycle fluctuations since the mid 1980s, see, among other Caldara et al. (2016). Some papers therefore focus on the impact of uncertainty on the macroeconomy (Bloom (2009), Caggiano et al. (2014), and Jurado et al. (2015)). Different from theirs, this chapter investigates the role of financial uncertainty as a conditional variable on the effectiveness of monetary policy shocks. This provides insights on how to implement monetary policy to stabilize the economy and stimulate the level of aggregate demand during times of stress. In general, uncertainty is associated with the effectiveness of monetary policy on real economy through the nonlinearities in two transmission channels: the interest rate and the credit channel. The interest rate channel claims that due to “wait and see” and uncertainty-dependent price-setting mechanism, the economy react weaker to monetary stimulus during high uncertainty periods. Whereas, the credit channel suggests that when

financial uncertainty heightens, firms are likely to suffer from the increasing external finance premium, therefore, an interest rate drop would cause firms react stronger compared to the periods with wide internal finance.

Chapter 4 therefore applies the smooth transition VAR to examine monetary policy shocks, in which the transition between different states depends on the financial uncertainty index of Ludvigson et al. (2015). This uncertainty index extracts the variance of the unforecastable components from a large financial dataset, including variables from the stock market, the bond market and commodity markets. The previous literature heavily employs the VIX index as the uncertainty indicator, which only focuses on the stock market and cannot distinguish expected and unexpected movements.

The results obtained in Chapter 4 imply that regardless of the financial uncertainty states, monetary stimulus has expansionary effect on the real economy and financial market. Nevertheless, monetary shocks have stronger, but less persistent, effects during periods of elevated financial uncertainty than during tranquil times. On the other hand, when the VIX index and the economic uncertainty index in Jurado et al. (2015) are used as the transition variable, the economy is less sensitive to expansionary monetary shocks during high uncertainty periods, consistent with the findings of Aastveit et al. (2017) and Pellegrino (2017). The results in Chapter 4 reconcile the conflicting explanations of the nonlinearities in the interest rate and the credit channel. Importantly, in the short run, the credit channel dominates so that an interest rate drop decreases the cost of credit more when financial uncertainty heightens. This further causes stronger reaction of the financial market and the real economy. In the long run, whereas, the interest rate prevails, making the monetary policy shocks less effective during high financial uncertainty periods.

This thesis sheds lights on the importance of financial markets on the real



economy. For instance, the stock return prediction method this thesis constructs has essential implications for investment, as well as monitoring ups and downs in the economy. Another point this thesis claims is that financial integration is linked to uncertainty, providing insights on risk management and policy implementation. In addition, uncertainty originated from the financial market has impact on the effectiveness of monetary policy.

# Appendix A

## Appendix of Chapter 2

This appendix contains more details of Chapter 2. Section A.1 and A.2 present the complete algorithms of dynamic linear models and dynamic mixture model averaging. Section A.3 shows the details of technical predictors. More economic evaluation and robustness checks results are presented as well.

### A.1 Dynamic Linear Models

We begin by transcribing the predictive regression from the methodological section in our main text. Assume  $r_t$  is the excess stock return at time  $t$ ,  $X_{t-1}$  is the specific predictor for each individual model at time  $t - 1$  and time-varying parameter models are allowed. We perform the return prediction as:

$$r_t = X_{t-1}\theta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, H_t) \quad (\text{observation equation}) \quad (\text{A.1})$$

$$\theta_t = \theta_{t-1} + u_t, \quad u_t \sim N(0, Q_t) \quad (\text{transition equation}) \quad (\text{A.2})$$

The important part of the dynamic linear model involves the priors for  $H_t$  and  $\theta_t$ , as well as an approach to estimate  $Q_t$ ; the conditional posterior distribution of  $H_t$  and  $\theta_t$ ; and the predictive density. Additionally, we also require an updating process for the priors after observing the data.

Given that we take a Bayesian perspective, denote  $D_t = [r_t, r_{t-1}, \dots, X_t, X_{t-1}, \dots]$  as the information set available at  $t$ , which includes all the previous information about excess stock return values, predictor values, as well as the priors for coefficients  $\theta_0$  and observational variance  $H_0$ . Following Raftery et al. (2010) and Koop and Korobilis (2012), we employ a simple Kalman filter algorithm, to incorporate forgetting factors  $\lambda$  into the evolution of the parameters and construct time-varying coefficients. For given values of  $H_t$  and  $Q_t$ , Kalman filtering starts with the posterior distribution for  $\theta_{t-1}$ :

$$\theta_{t-1}|D_{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}) \quad (\text{A.3})$$

Then Kalman filter predicts  $\theta_t$  conditional on the information up to time  $t - 1$ :

$$\theta_t|D_{t-1} \sim N(\hat{\theta}_{t-1}, \Sigma_{t|t-1}) \quad (\text{A.4})$$

where

$$\Sigma_{t|t-1} = \Sigma_{t-1|t-1} + Q_t \quad (\text{A.5})$$

Instead of specifying the matrix  $Q_t$ , Raftery et al. (2010) and Koop and Korobilis (2012) suggest using a form of forgetting factor to avoid MCMC and ease computational demands. In particular, Equation (A.5) is replaced by:

$$\Sigma_{t|t-1} = \frac{1}{\lambda} \Sigma_{t-1|t-1}, \quad 0 < \lambda \leq 1 \quad (\text{A.6})$$

or, equivalently,

$$Q_t = (\lambda^{-1} - 1) \Sigma_{t-1|t-1} \quad (\text{A.7})$$

where  $\lambda$  is the forgetting factor. Based on Equation (A.7), we infer that constant coefficients models correspond to  $Q_t = 0$  and  $\lambda = 1$ . In cases when  $\lambda < 1$  implies that  $Q_t > 0$ , thus, covariances  $\Sigma_{t|t-1}$  increase over time and coefficients

are time-varying. The lower the value of  $\lambda$ , the more sudden the coefficients change. The forgetting factor  $\lambda$  has a substantial influence on coefficient stability and different degrees of  $\lambda$  lead to different dynamic linear models.

Finally, the estimation process is completed by the updating equation:

$$\theta_t|D_t \sim N(\hat{\theta}_t, \Sigma_{t|t}) \quad (\text{A.8})$$

where

$$\hat{\theta}_t = \hat{\theta}_{t-1} + \Sigma_{t|t-1} X'_{t-1} (H_t + X_{t-1} \Sigma_{t|t-1} X'_{t-1})^{-1} (r_t - X_{t-1} \hat{\theta}_{t-1}) \quad (\text{A.9})$$

and

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} X'_{t-1} (H_t + X_{t-1} \Sigma_{t|t-1} X'_{t-1})^{-1} X_{t-1} \Sigma_{t|t-1} \quad (\text{A.10})$$

Therefore, conditional on  $H_t$ , given the prior of  $\theta_0$ , the predicting equations (A.4) and (A.6), and the updating equation (A.8), the predictive distribution can be obtained over time as:

$$r_t|D_{t-1} \sim N(X_t \hat{\theta}_{t-1}, H_t + X_t \Sigma_{t|t-1} X'_t) \quad (\text{A.11})$$

Note that all the derivations are conditional on  $H_t$ , the observational variance. Evidence for time-varying volatility is strong as it generates fat-tailed return distribution for stock market (Johannes et al., 2014). Moreover, numerous studies find the important role time-varying volatility plays in predicting excess stock return (see, for example, Johannes et al. (2014) and Joscha and Schüssler (2014)). Theoretically, stochastic volatility or ARCH specification could be used for  $H_t$ . But this would significantly increase the computational

burden. We follow Koop and Korobilis (2012) and Byrne et al. (2018) to estimate  $H_t$  using Exponentially Weighted Moving Average (EWMA), which is a common approach to model time-varying volatilities in finance. Importantly, it updates at each time and can be approximated by a recursive form:

$$\hat{H}_{t+1|t} = \kappa \hat{H}_{t|t-1} + (1 - \kappa)(r_t - X_{t-1}\hat{\theta}_t)^2 \quad (\text{A.12})$$

where  $\kappa$  is referred to as the delay factor. We set  $\kappa = 0.95$  for monthly data. This fits monthly data's property: a relatively rapid delay. In Appendix A.6, we further check the importance and specification of time-varying volatility, by comparing the results of DMMA with those of constant volatility and the stochastic volatility model suggested by Stock and Watson (2007).

## A.2 Dynamic Mixture Model Averaging

Denote  $k_i$  as a certain choice of predictive variables from the  $K$  candidates,  $\lambda_j$  as a certain selection of degree of time-variation in coefficients from the set  $\{\lambda_1, \lambda_2, \dots, \lambda_d\}$  and  $\alpha_z$  as a specific choice of degree of time-variation in forecasting models from the space  $\{\alpha_1, \alpha_2, \dots, \alpha_a\}$ . Certainly, the choices of  $k_i$  and  $\lambda_j$  affect the predictive density of the individual dynamic models, and the choice of  $\alpha_z$  influences the weight assigned to each predictive model thus the final forecasting result. Hence, the one-step ahead prediction of excess stock returns conditional on  $k_i, \lambda_j$  and  $\alpha_z$  is:

$$\hat{r}_{t,i}^{j,z} = E(r_t \mid k_i, \lambda_j, \alpha_z, D_{t-1}) = X_{t-1}\hat{\theta}_{t-1} \mid k_i, \lambda_j, \alpha_z, D_{t-1} \quad (\text{A.13})$$

The starting point in examining the importance of different model features,

is to assign prior to each predictor  $k_i$ , each support point  $\lambda_j$  and  $\alpha_z$ . We assume each predictor and each support point to have the same weight at the beginning. That is, for each  $k_i$ ,  $\lambda_j$  and  $\alpha_z$ , uninformative priors are set:

$$P(\alpha_z \mid D_0) = 1/a, \quad (\text{A.14})$$

$$P(\lambda_j \mid \alpha_z, D_0) = 1/d, \quad (\text{A.15})$$

$$P(k_i \mid \lambda_j, \alpha_z, D_0) = 1/K \quad (\text{A.16})$$

Following Raftery et al. (2010) and Koop and Korobilis (2012), model prediction equation for different predictors  $k_i$ , given the degree of time variation in coefficients  $\lambda_j$  and in forecasting models  $\alpha_z$  at time  $t$  is:

$$P(L_t = k_i \mid \lambda_j, \alpha_z, D_{t-1}) = \frac{P(L_{t-1} = k_i \mid \lambda_j, \alpha_z, D_{t-1})^{\alpha_z}}{\sum_{k_i} P(L_{t-1} = k_i \mid \lambda_j, \alpha_z, D_{t-1})^{\alpha_z}} \quad (\text{A.17})$$

where  $L_t$  indicates certain model specification selected at time  $t$  and  $\alpha_z$  is the other forgetting factor. The advantage of using forgetting factor  $\alpha_z$  is that MCMC algorithm is not required to draw transition probabilities between different model specifications.

At time  $t$ , the posterior probabilities are updated based on Bayes' rule. We first update the conditional posterior probability of a certain predictor, given value of  $\lambda_j$  and  $\alpha_z$ :

$$P(L_t = k_i \mid \lambda_j, \alpha_z, D_t) = \frac{P(r_t \mid L_t = k_i, \lambda_j, \alpha_z, D_{t-1})P(L_t = k_i \mid \lambda_j, \alpha_z, D_{t-1})}{P(r_t \mid \lambda_j, \alpha_z, D_{t-1})} \quad (\text{A.18})$$

where

$$P(r_t \mid \lambda_j, \alpha_z, D_{t-1}) = \sum_{k_i} P(r_t \mid L_t = k_i, \lambda_j, \alpha_z, D_{t-1})P(L_t = k_i \mid \lambda_j, \alpha_z, D_{t-1}) \quad (\text{A.19})$$

and importantly, the conditional density given by Equation (A.11) in Appendix A.1 is:

$$P(r_t \mid L_t = k_i, \lambda_j, \alpha_z, D_{t-1}) \sim N(\hat{r}_{t,i}^{j,z}, H_t + X_{t-1} \Sigma_{t|t-1} X'_{t-1}) \quad (\text{A.20})$$

As we mentioned above, the one-step ahead prediction of excess stock returns conditional on  $k_i, \lambda_j, \alpha_z$  and the previous information set  $D_{t-1}$  is:

$$\hat{r}_{t,i}^{j,z} = E(r_t \mid k_i, \lambda_j, \alpha_z, D_{t-1}) = X_{t-1} \hat{\theta}_{t-1} \mid k_i, \lambda_j, \alpha_z, D_{t-1} \quad (\text{A.21})$$

Given  $\lambda_j$  and  $\alpha_z$ , the prediction over all the different predictors at time  $t$  is :

$$\hat{r}_t^{j,z} = \sum_{k_i} P(L_t = k_i \mid \lambda_j, \alpha_z, D_{t-1}) \hat{r}_{t,i}^{j,z} \quad (\text{A.22})$$

Therefore, for each specific  $\lambda_j$  and  $\alpha_z$ , the prediction results are the weighted average of the forecasts of the individual predictors using their posterior probability. As several possible values for  $\lambda$  and  $\alpha$  are considered, we also perform Bayesian averaging over them.

Starting with the prior probability in Equation (A.15), the posterior probability for  $\lambda_j$  given a specific choice of  $\alpha_z$  is:

$$P(\lambda_j \mid \alpha_z, D_t) = \frac{P(r_t \mid \lambda_j, \alpha_z, D_{t-1}) P(\lambda_j \mid \alpha_z, D_{t-1})}{P(r_t \mid \alpha_z, D_{t-1})} \quad (\text{A.23})$$

where

$$P(r_t \mid \alpha_z, D_{t-1}) = \sum_{\lambda_j} P(r_t \mid \lambda_j, \alpha_z, D_{t-1}) P(\lambda_j \mid \alpha_z, D_{t-1}) \quad (\text{A.24})$$

The prediction of the average model for each of the specific value of  $\alpha_z$  is:

$$\hat{r}_t^z = \sum_{\lambda_j} P(\lambda_j \mid \alpha_z, D_{t-1}) \hat{r}_t^{j,z} \quad (\text{A.25})$$

Finally, the posterior probability for a certain  $\alpha_z$  is obtained:

$$P(\alpha_z \mid D_t) = \frac{P(r_t \mid \alpha_z, D_{t-1})P(\alpha_z \mid D_{t-1})}{P(r_t \mid D_{t-1})} \quad (\text{A.26})$$

where

$$P(r_t \mid D_{t-1}) = \sum_{\alpha_z} P(r_t \mid \alpha_z, D_{t-1})P(\alpha_z \mid D_{t-1}) \quad (\text{A.27})$$

We note that based on Equation (A.23) and (A.26), we can ascertain the degree of time-variation in coefficients and in forecasting models supported by the data. Importantly, the unconditional prediction of all the model specifications is :

$$\hat{r}_t = \sum_{\alpha_z} P(\alpha_z \mid D_{t-1}) \hat{r}_t^z \quad (\text{A.28})$$

Hence,  $\hat{r}_t$  is obtained by averaging over the average predictors' prediction, over degrees of time-variation in coefficients and in forecasting models.

The total posterior of a model specification (i.e., choice of predictive variables  $k_i$ , choice of  $\lambda_j$  and choice of  $\alpha_z$ ) can be obtained according to the Bayes' rule:

$$\begin{aligned} P(k_i, \lambda_j, \alpha_z \mid D_t) &= P(k_i, \lambda_j \mid \alpha_z, D_t)P(\alpha_z \mid D_t) \\ &= P(k_i \mid \lambda_j, \alpha_z, D_t)P(\lambda_j \mid \alpha_z, D_t)P(\alpha_z \mid D_t) \end{aligned} \quad (\text{A.29})$$

### A.3 Construction of Technical Predictors

We form 14 technical predictors based on three technical strategies following Neely et al. (2014).



The first strategy is to compare two moving-averages ( $MA$ ):

$$S_{i,t} = \begin{cases} 1 & \text{if } MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if } MA_{s,t} < MA_{l,t} \end{cases},$$

where

$$MA_{j,t} = (1/j) \sum_{i=0}^{j-1} P_{t-i}, \quad j = s, l, \quad s = 1, 2, 3 \quad l = 9, 12$$

We obtain a buy signal when  $S_{i,t} = 1$  or a sell signal when  $S_{i,t} = 0$ . A  $MA$  indicator with  $s$  and  $l$  lags can be presented as  $MA(s, l)$ .

The second strategy is based on momentum ( $MOM$ ):

$$S_{i,t} = \begin{cases} 1 & \text{if } P_t \geq P_{t-m} \\ 0 & \text{if } P_t < P_{t-m} \end{cases}, \quad m = 9, 12$$

When the current stock price is higher than that  $m$  period ago, it generates a positive momentum, therefore, a buy signal. The indicator is  $MOM(m)$ .

The last strategy is based on volume ( $VOL$ ). Define:

$$OBV_t = \sum_{k=1}^t VOL_k D_k, \quad D_k = \begin{cases} 1 & \text{if } P_k \geq P_{k-1} \\ -1 & \text{if } P_k < P_{k-1} \end{cases}$$

where  $VOL_k$  is the trading volume of stocks during period  $k$ . We then construct a trading signal based on  $OBV_t$ :

$$S_{i,t} = \begin{cases} 1 & \text{if } MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 & \text{if } MA_{s,t}^{OBV} < MA_{l,t}^{OBV} \end{cases},$$

where

$$MA_{j,t}^{OBV} = (1/j) \sum_{i=0}^{j-1} OBV_{t-i}, \quad j = s, l, \quad s = 1, 2, 3 \quad l = 9, 12$$

If volume and prices are both high recently, this implies a positive trend, and thus, generates a buy signal. We denote the indicator as  $VOL(s, l)$ .

## A.4 Economic Evaluation for Different Sets of Predictors and Univariate Models

Table A.1 presents the economic evaluation using macroeconomic or (and) technical predictors. In general, results are in line with the findings from the statistical evaluation. DMMA has the best or slightly lower certainty equivalent return and sharp return than the best nested model. Combining different information from macroeconomic and technical predictors decreases model uncertainty and improves the economic value of the results. However, for period 1960+ and period 1988+, technical indicators alone perform slightly better.

We further employ univariate analysis and investigate whether time-varying coefficients is important economically. Table A.2 shows the certainty equivalent return ( $CER$ ) of single-predictor models including or excluding time-varying coefficients. Models including time-varying coefficients perform better than those with constant coefficients. Across different predictor sets, single technical indicators have higher certainty equivalent return compared with single macroeconomic predictors, especially for the subsample 1988+. Combining different predictors within the macroeconomic (technical) dataset improves the economic gain.

## **A.5 Results for Dynamic Model Mixture Selection (DMMS)**

Dynamic model mixture selection (DMMS), different from DMMA, selects the individual model with the highest posterior probability at each time, among choices of predictors, degrees of time variation in coefficients and forecasting models. Table A.3 presents the statistical and economical results for DMMS. Compared with the results in Table 2.3 and 2.6, we find that although DMMS occasionally outperforms HM in terms of log likelihoods and certainty equivalent return, it is worse than DMMA. We conclude that this is because DMMS switches more rapidly than DMMA and cannot make use of all the information data provides.

## **A.6 Empirical Robustness Checks**

In this section of Appendix, we employ several robustness checks. We first relax the assumption that time-varying coefficients in the state space model follow a random walk process (see Equation (2.2) in Section 2.2.1). Then we investigate the importance of time-varying volatility and the validity of modeling volatility using Exponentially Weighted Moving Average estimator (EWMA) in Appendix A.1. We also present the 3-month and 6-month ahead statistical and economical evaluation.

We start by checking whether the results are sensitive to random walk assumption and address the stationary issue using autoregressive process for the transition equation, as the asset pricing theory suggests that expected returns are nonstationary. Specially, following Dangl and Halling (2012), we rewrite

our transition equation by introducing autoregression in the following form:

$$\theta_t = G\mathbb{I}\theta_{t-1} + u_t \quad (\text{A.1})$$

with  $\mathbb{I}$  denoting an identity matrix and  $0 < G \leq 1$  a scalar. Hence, if  $G = 1$ , Equation (A.1) is the same as Equation (2.2). We also consider several alternatives of  $G$ , including  $G = 0.95, 0.90, 0.80$  to generate nonstationary process. Our goal is to compare the results of random walk coefficients and any other parameters choices of  $G$ .

From Table A.4, in the race between random walk coefficients and autoregressive coefficients, model with random walk coefficients works better than any parameter choice of  $G$  less than one. DMMA model with random walk coefficients consistently has the highest out-of-sample  $R_{OS}^2$  and predictive log likelihoods over different sample periods. Regarding economic evaluation, in Table A.5, model with random walk coefficients is the only one that could consistently outperform HM according to  $CER$  and  $SR$ . Furthermore, except for the  $CER$  in the period of 1960+, DMMA model with random walk coefficients dominates other autoregression coefficients. All these demonstrate the advantage of applying random walk coefficients.

Then, we study the importance of time-varying volatility and present the results of constant volatility and the volatility constructed using the UC-SV model of Stock and Watson (2007) in Table A.6. Clearly, imposing constant volatility deteriorates the forecasting results, implying the evidence of time-varying volatility, which is an important feature for stock markets. Even though the stochastic volatility (SV) method requires MCMC and significantly increases the computational burden, we obtain similar results compared to our baseline results using EWMA.

We obtain quantitatively similar results for the 3-month and 6-month ahead

statistical and economical evaluation compared to one-step ahead baseline results. DMMA still outperforms alternatives model specifications statistically and economically, with the highest out-of-sample  $R_{OS}^2$ , predictive likelihoods and  $CER$ .

TABLE A.1: Economic Evaluation Using Different Sets of Predictors

	Period:1960+		Period:1976+		Period:1988+	
	CER	SR	CER	SR	CER	SR
Panel A: Macroeconomic Predictors						
DMMA	<b>5.11</b>	<b>0.09</b>	<b>6.16</b>	<b>0.11</b>	<b>7.10</b>	<b>0.14</b>
EW	<b>5.01</b>	<b>0.09</b>	<b>6.12</b>	<b>0.10</b>	<b>7.02</b>	<b>0.14</b>
EW-CC	<b>4.26</b>	<b>0.08</b>	<b>4.68</b>	<b>0.09</b>	<b>5.77</b>	0.12
BMA	<b>5.08</b>	<b>0.08</b>	<b>4.70</b>	0.08	4.84	0.11
BMA-CC	2.48	0.03	2.96	0.05	4.58	0.10
Panel B: Technical Indicators						
DMMA	<b>5.19</b>	<b>0.09</b>	<b>6.20</b>	<b>0.11</b>	<b>7.51</b>	<b>0.16</b>
EW	<b>5.21</b>	<b>0.09</b>	<b>6.01</b>	<b>0.11</b>	<b>7.38</b>	<b>0.16</b>
EW-CC	2.47	0.06	<b>5.93</b>	<b>0.10</b>	<b>7.20</b>	<b>0.16</b>
BMA	<b>5.20</b>	<b>0.09</b>	<b>6.06</b>	<b>0.10</b>	<b>7.21</b>	<b>0.15</b>
BMA-CC	<b>4.44</b>	<b>0.08</b>	<b>6.01</b>	<b>0.10</b>	<b>7.20</b>	<b>0.16</b>
Panel C: Macro Plus Technical Indicators						
DMMA	<b>5.15</b>	<b>0.08</b>	<b>6.24</b>	<b>0.10</b>	<b>7.41</b>	<b>0.15</b>
EW	<b>5.44</b>	<b>0.09</b>	<b>6.34</b>	<b>0.11</b>	<b>7.26</b>	<b>0.14</b>
EW-CC	<b>4.15</b>	0.07	<b>5.54</b>	<b>0.10</b>	<b>7.09</b>	<b>0.14</b>
BMA	<b>5.04</b>	0.07	<b>5.56</b>	<b>0.09</b>	<b>6.30</b>	<b>0.13</b>
BMA-CC	2.49	0.03	<b>4.13</b>	0.07	<b>5.74</b>	0.12
HM	3.39	0.07	3.93	0.08	5.25	0.12

*Notes* : Economic evaluation using different sets of predictors. We only use macroeconomic predictors in Panel A, only employ technical indicators in Panel B and combine all the predictors in Panel C. See more details about the economic evaluation in Table 2.6.

TABLE A.2: Economic Evaluation of Single-Predictor Models Including or Excluding Tvar-Coeffs

Panel A: Macroeconomic Predictors						
	Models incl. TVar-Coeff			Models excl. TVar-Coeff.		
	1960+	1976+	1988+	1960+	1976+	1988+
dy	3.86	<b>6.09</b>	4.81	3.09	<b>4.12</b>	1.36
ep	<b>5.44</b>	<b>6.06</b>	<b>6.33</b>	<b>5.75</b>	<b>5.88</b>	<b>6.30</b>
de	<b>4.67</b>	<b>6.03</b>	<b>5.33</b>	<b>3.63</b>	3.43	1.30
svar	1.91	<b>4.37</b>	<b>5.22</b>	3.28	<b>4.65</b>	<b>5.43</b>
bm	1.35	3.47	3.31	3.25	3.39	3.47
ntis	<b>4.32</b>	<b>5.17</b>	<b>5.62</b>	2.92	<b>3.97</b>	3.78
tbl	<b>4.08</b>	<b>4.69</b>	<b>5.78</b>	<b>5.86</b>	<b>5.21</b>	<b>5.44</b>
lty	<b>4.51</b>	<b>5.46</b>	3.78	<b>4.76</b>	<b>4.74</b>	3.96
ltr	3.11	3.33	2.31	<b>4.83</b>	3.06	1.70
dfy	<b>3.48</b>	<b>5.02</b>	<b>5.64</b>	2.91	<b>4.14</b>	4.39
dfr	2.74	3.84	4.05	2.84	3.46	<b>5.80</b>
infl	<b>3.80</b>	<b>4.59</b>	3.81	3.18	<b>4.06</b>	3.85
Panel A: Technical Indicators						
	Models incl. TVar-Coeff			Models excl. TVar-Coeff.		
	1960+	1976+	1988+	1960+	1976+	1988+
MA(1,9)	<b>4.19</b>	<b>5.24</b>	<b>5.95</b>	2.46	<b>5.23</b>	<b>5.77</b>
MA(2,9)	<b>5.62</b>	<b>6.69</b>	<b>7.39</b>	<b>4.53</b>	<b>6.80</b>	<b>7.25</b>
MA(3,9)	3.35	<b>5.25</b>	<b>5.08</b>	2.61	<b>5.46</b>	<b>5.87</b>
MA(1,12)	<b>6.04</b>	<b>7.09</b>	<b>7.84</b>	<b>6.34</b>	<b>7.42</b>	<b>7.72</b>
MA(2,12)	<b>5.46</b>	<b>5.17</b>	<b>5.72</b>	<b>5.76</b>	<b>5.38</b>	<b>5.68</b>
MA(3,12)	<b>3.97</b>	<b>4.52</b>	<b>5.38</b>	2.26	<b>4.04</b>	<b>5.64</b>
MOM(9)	<b>3.99</b>	<b>4.22</b>	<b>5.79</b>	2.26	<b>4.46</b>	4.96
MOM(12)	<b>3.84</b>	<b>4.25</b>	<b>5.73</b>	2.17	3.83	4.94
VOL(1,9)	<b>3.63</b>	<b>5.35</b>	4.67	3.03	<b>4.15</b>	4.68
VOL(2,9)	<b>5.05</b>	<b>5.66</b>	<b>5.67</b>	2.53	<b>6.16</b>	<b>6.15</b>
VOL(3,9)	<b>4.90</b>	<b>6.02</b>	<b>5.38</b>	3.14	3.67	<b>5.51</b>
VOL(1,12)	<b>4.68</b>	<b>6.06</b>	<b>6.61</b>	3.07	3.44	5.00
VOL(2,12)	<b>4.14</b>	<b>5.47</b>	4.91	3.07	<b>3.99</b>	<b>4.55</b>
VOL(3,12)	<b>5.17</b>	<b>5.59</b>	<b>7.43</b>	2.40	<b>5.31</b>	<b>7.15</b>
HM	3.39	3.93	5.25	3.39	3.93	5.25

*Notes :* Certainty equivalent return (CER) of single-predictor models including or excluding time-varying coefficients. See more details about the economic evaluation in Table 2.6.

TABLE A.3: Evaluation for Dynamic Mixture Model Selection (DMMS)

	Period:1960+		Period:1976+		Period:1988+	
	Statistical Evaluation					
	$R_{OS}^2$	$Log(PL)$	$R_{OS}^2$	$Log(PL)$	$R_{OS}^2$	$Log(PL)$
DMMS	-0.79	<b>1141.20</b>	-4.74	<b>796.58</b>	-5.22	<b>568.71</b>
	Economic Evaluation					
	$CER$	$SR$	$CER$	$SR$	$CER$	$SR$
DMMS	<b>5.11</b>	0.06	<b>4.91</b>	0.05	0.22	0.01

*Notes:* Statistical predictability for dynamic mixture model selection (DMMS). See details in Table 2.3.



TABLE A.4: Statistical Evaluation of Different Time-Varying Coefficients Process

	Period:1960+		Period:1976+		Period:1988+	
	$R_{OS}^2$	$Log(PL)$	$R_{OS}^2$	$Log(PL)$	$R_{OS}^2$	$Log(PL)$
$G = 1.00$	<b>1.72**</b>	<b>1141.70</b>	<b>0.91*</b>	<b>802.66</b>	<b>0.88*</b>	<b>573.13</b>
$G = 0.95$	-0.63	<b>1140.50</b>	-0.57	<b>802.00</b>	-0.67	<b>571.56</b>
$G = 0.90$	-0.76	<b>1139.80</b>	-0.39	<b>801.88</b>	-0.35	<b>571.77</b>
$G = 0.80$	-0.37	<b>1141.40</b>	-0.24	<b>801.85</b>	-0.20	<b>571.60</b>
HM	0	128.56	0	293.27	0	304.43

*Notes:* Statistical predictability for different models using various autoregression coefficient ( $G$ ). See details in Table 2.3.

TABLE A.5: Economic Evaluation of Different Time-Varying Coefficients Process

	Period:1960+		Period:1976+		Period:1988+	
	<i>CER</i>	<i>SR</i>	<i>CER</i>	<i>SR</i>	<i>CER</i>	<i>SR</i>
$G = 1.00$	<b>5.15</b>	<b>0.08</b>	<b>6.24</b>	<b>0.10</b>	<b>7.41</b>	<b>0.15</b>
$G = 0.95$	<b>5.34</b>	0.06	3.17	0.02	<b>6.37</b>	<b>0.13</b>
$G = 0.90$	<b>5.18</b>	0.06	2.94	0.02	<b>6.50</b>	<b>0.13</b>
$G = 0.80$	<b>5.62</b>	0.07	1.78	0.00	<b>5.37</b>	0.11
HM	3.39	0.07	3.93	0.08	5.25	0.12

*Notes :* Economic predictability for different predictive models various autoregression coefficient ( $G$ ). See details in Table 2.6.

TABLE A.6: Statistical and Economic Evaluation of Different Volatility Specifications

	Period:1960+		Period:1976+		Period:1988+	
	$R_{OS}^2(\%)$	$CER$	$R_{OS}^2(\%)$	$CER$	$R_{OS}^2(\%)$	$CER$
EWMA	<b>1.72**</b>	<b>5.15</b>	<b>0.91*</b>	<b>6.24</b>	<b>0.88*</b>	<b>7.41</b>
SV	<b>1.87*</b>	<b>5.20</b>	<b>1.05**</b>	<b>6.19</b>	<b>0.79*</b>	<b>7.50</b>
CV	<b>0.24</b>	<b>5.03</b>	<b>0.64*</b>	<b>6.00</b>	<b>0.30</b>	<b>6.87</b>
HM	0	3.39	0	3.93	0	5.25

*Notes* : Statistical and economic evaluation of different volatility specifications. EWMA represents the Exponentially Weighted Moving Average estimator we employ in the paper. SV refers to the stochastic volatility method used in Stock and Watson (2007), where the time-varying coefficients and forecasting models remain the same as DMMA and the 50,000 draws are made for MCMC, with the first 45,000 as burn-in draws. See details about  $R_{OS}^2(\%)$  and  $CER$  in Table 2.3 and 2.6.

TABLE A.7: 3-Month and 6-Month Ahead Statistical and Econo-  
mical Evaluation

Panel A: Dynamic Mixture Model Averaging (DMMA)								
DMMA	3-month ahead				6-month ahead			
	$R^2_{OS}(\%)$	$Log(PL)$	$CER$	$SR$	$R^2_{OS}(\%)$	$Log(PL)$	$CER$	$SR$
	<b>1.51**</b>	<b>1140.50</b>	<b>5.16</b>	<b>0.08</b>	<b>1.78**</b>	<b>1134.60</b>	<b>5.08</b>	<b>0.08</b>
Panel B: Equal Weights (EW)								
EW	<b>1.34**</b>	<b>1140.30</b>	<b>4.65</b>	<b>0.08</b>	<b>1.43*</b>	<b>1133.80</b>	<b>4.36</b>	<b>0.08</b>
EW-CC	<b>0.52*</b>	<b>1137.90</b>	<b>3.27</b>	0.07	<b>0.24*</b>	<b>1130.00</b>	<b>3.18</b>	0.07
Panel C: Bayesian Model Averaging (BMA)								
BMA	-0.76	<b>1131.20</b>	<b>4.47</b>	<b>0.06</b>	<b>0.37</b>	<b>1128.60</b>	<b>3.67</b>	0.05
BMA-CC	-0.62	<b>1129.50</b>	3.11	0.05	-0.45	<b>1124.00</b>	<b>3.23</b>	0.04
Panel D: Dynamic Model Averaging								
$\lambda=0.90, \alpha=0.90$	-9.84	<b>1090.60</b>	2.27	0.02	-8.65	<b>1082.30</b>	<b>4.29</b>	0.07
$\lambda=0.95, \alpha=0.90$	-5.63	<b>1114.60</b>	<b>3.35</b>	0.04	-4.03	<b>1107.80</b>	<b>4.52</b>	<b>0.08</b>
$\lambda=0.99, \alpha=0.90$	-0.43	<b>1134.60</b>	<b>3.66</b>	0.05	-0.28	<b>1128.00</b>	<b>3.45</b>	0.05
$\lambda=0.90, \alpha=0.95$	-11.20	<b>1088.50</b>	2.91	0.03	-9.41	<b>1079.20</b>	<b>4.55</b>	<b>0.08</b>
$\lambda=0.95, \alpha=0.95$	-6.20	<b>1113.20</b>	<b>3.80</b>	0.05	-5.66	<b>1105.40</b>	<b>4.91</b>	<b>0.09</b>
$\lambda=0.99, \alpha=0.95$	-0.55	<b>1133.90</b>	<b>3.55</b>	0.05	-0.48	<b>1127.10</b>	<b>3.31</b>	0.04
$\lambda=0.90, \alpha=0.99$	-11.90	<b>1086.40</b>	<b>3.21</b>	0.04	-8.88	<b>1078.00</b>	<b>4.69</b>	0.06
$\lambda=0.95, \alpha=0.99$	-6.90	<b>1111.80</b>	<b>3.84</b>	0.05	-4.91	<b>1106.20</b>	<b>4.82</b>	<b>0.09</b>
$\lambda=0.99, \alpha=0.99$	-0.80	<b>1132.30</b>	<b>3.43</b>	0.05	-0.67	<b>1125.80</b>	<b>4.30</b>	0.06
HM	0	130.29	3.19	0.07	0	83.60	3.06	0.07

Notes: The table shows the 3-month and 6-month ahead statistical and economical evaluation. The statistical evaluation includes out-of-sample  $R^2$  ( $R^2_{OS}(\%)$ ), Clark and West test (\*, \*\* and \*\*\* show that the null hypothesis that the MSFE of HM is less than or equal to that of predictive model, is rejected at the 10%, 5% and 1% significance level, respectively) and predictive log likelihoods ( $Log(PL)$ ). The economic evaluation includes the certainty equivalent return ( $CER$ ) and monthly Sharpe Ratio ( $SR$ ) compared with a historical mean model (HM) for a mean-variance investor who allocates wealth between equities and risk-free assets using different forecasts from different models. We consider different model combination methods, including combination with equal weights (EW) in Panel B, Bayesian model averaging (BMA) in Panel C and also all the possible dynamic model averaging (DMA) models in Panel D. Bold font suggests the statistics of that predictive model is larger than the corresponding one of HM. The sample period is 1960+.

## Appendix B

### Appendix of Chapter 3

This appendix contains more details of Chapter 3. Section B.1 shows our main algorithm to measure financial integration: time-varying coefficients model with stochastic volatility. Section B.2 and B.3 present the techniques for financial integration prediction. Tables and figures show additional results including data description, trend and break tests, Granger causality test, and components in our main model.

#### B.1 Detailed Estimation of The Time-varying Coefficients Model with Stochastic Volatility

Following Blake and Mumtaz (2012), we implement our time-varying coefficients model with stochastic volatility for each economy we consider, based on Metropolis-Hastings algorithm and Carter and Kohn (1994) algorithm.

- Step 1 Time 0

Conditional on  $g$  and  $B_t$  sample  $h_0$ , the initial value of  $h_t$  from the log normal density is:

$$f(h_0 | h_1) = h_0^{-1} \exp\left(\frac{-(\ln h_0 - \mu_0)^2}{2\sigma_0}\right) \quad (\text{B.1})$$

where  $\mu_0 = \sigma(\frac{\bar{\mu}}{\bar{\sigma}} + \frac{\ln h_1}{g})$  and  $\sigma_0 = \frac{\bar{\sigma}g}{\bar{\sigma}+g}$ .

- Step 1 Time 1 to T-1

Conditional on  $g$  and  $B_t$  draw a new  $h_t$  for each time period  $t = 1$  to  $T-1$  from the candidate density:

$$q(\Phi^{G+1}) = h_t^{-1} \exp\left(\frac{-(\ln h_t - \mu)^2}{2\sigma_h}\right) \quad (\text{B.2})$$

where  $\mu = \frac{\ln h_{t+1} + \ln h_{t-1}}{2}$  and  $\sigma_h = \frac{g}{2}$ . Calculate the acceptance probability:

$$\alpha = \min\left(\frac{h_{t,new}^{0.5} \exp(\frac{-\varepsilon_t^2}{2h_{t,new}})}{h_{t,old}^{0.5} \exp(\frac{-\varepsilon_t^2}{2h_{t,old}})}, 1\right) \quad (\text{B.3})$$

Draw  $u \sim U(0, 1)$ . If  $u < \alpha$ , set  $h_t = h_{t,new}$ . Otherwise retain the old draw  $h_{t,old}$ .

- Step 1 Time T

For  $t = T$ ,  $\mu = \ln h_{t-1}$  and  $\sigma_h = g$ . Draw  $h_{t,new}$  from the candidate density:

$$q(\Phi^{G+1}) = h_t^{-1} \exp\left(\frac{-(\ln h_t - \mu)^2}{2\sigma_h}\right) \quad (\text{B.4})$$

Calculate the acceptance probability:

$$\alpha = \min\left(\frac{h_{t,new}^{0.5} \exp(\frac{-\varepsilon_t^2}{2h_{t,new}})}{h_{t,old}^{0.5} \exp(\frac{-\varepsilon_t^2}{2h_{t,old}})}, 1\right) \quad (\text{B.5})$$

Draw  $u \sim U(0, 1)$ . If  $u < \alpha$ , set  $h_t = h_{t,new}$ . Otherwise retain the old draw  $h_{t,old}$ .

- Step 2 Given a draw for  $h_t$ , compute  $v_t = \ln h_t - \ln h_{t-1}$ . Draw  $g$  from the following inverse Gamma distribution

$$g \sim IG\left(\frac{v_t'v_t + g_0}{2}, \frac{T + v_0}{2}\right) \quad (\text{B.6})$$

- Step 3 Conditional on  $h_t$  and  $Q$ , sample  $B_t$  using Carter and Kohn (1994) algorithm.
- Step 4 Conditional on  $B_t$ , sample  $Q$  from the inverse Wishart distribution with scale matrix  $(B_t - B_{t-1})'(B_t - B_{t-1}) + Q_0$  and degrees of freedom  $T_0 + T$ .
- Step 5 Repeat step 1 to step 4 50,000 times. We keep the last 5,000 draws of  $h_t, g, B_t$  and  $Q$  to compute the marginal posterior distributions.

## B.2 Dynamic Linear Model

We set a natural conjugate  $g$ -prior specification of the prior information for observational variance and coefficients:

$$V \mid D_0 \sim IG\left[\frac{1}{2}, \frac{1}{2}S_0\right] \quad (\text{B.7})$$

$$\theta_0 \mid D_0, V \sim N[0, gS_0(Z'Z)^{-1}] \quad (\text{B.8})$$

where

$$S_0 = \frac{1}{N-1}TVI'(I - Z(Z'Z)^{-1}Z')TVI \quad (\text{B.9})$$

This is a noninformative prior under the null-hypothesis of no-predictability and  $g$  is the scaling factor that measures the confidence attached to the null-hypothesis. We perform the prediction procedure with  $g=50$ .

The posteriors of unobservable coefficients  $\theta_{t-1} \mid D_t$  and the observational variance  $V \mid D_t$  are of the following forms:

$$V \mid D_t \sim IG\left[\frac{n_t}{2}, \frac{n_t S_t}{2}\right], \quad n_{t+1} = n_t + 1 \quad (\text{B.10})$$

$$\theta_{t-1} \mid D_t, V \sim N[\hat{\theta}_t, VC_t^*] \quad (\text{B.11})$$

where  $S_t$  is the mean of the observational variance  $V$  at time  $t$ ,  $n_t$  is the degree of freedom and  $C_t^*$  is the conditional covariance of  $\theta_{t-1}$  normalized by  $V$ . The vector of coefficients  $\theta_t$  is updated using Kalman filter

$$\theta_{t-1} \mid D_t \sim T_{n_t}[\hat{\theta}_t, S_t C_t^*] \quad (\text{B.12})$$

$$\theta_t \mid D_t \sim T_{n_t}[\hat{\theta}_t, R_t], \quad R_t = S_t C_t^* + W_t \quad (\text{B.13})$$

where

$$\hat{\theta}_{t+1} = \hat{\theta}_t + R_t Z_t Q_{t+1}^{-1} e_{t+1} \quad (\text{B.14})$$

$$R_{t+1} = \frac{1}{\delta} (R_t - R_t Z_t Q_{t+1}^{-1} Z_t' R_t') \quad (\text{B.15})$$

$$e_{t+1} = TVI_{t+1} - \widehat{TVI}_{t+1} \quad (\text{B.16})$$

$$Q_{t+1} = Z_t' R_t Z_t + S_t \quad (\text{B.17})$$

and we assume the estimate of the observational variance  $S_t$  is constant. The predictive density is given by:

$$\begin{aligned} f(TVI_{t+1} \mid D_t) &= \int_0^\infty \left[ \int_\theta \varphi(TVI_t; Z_t' \theta, V) \varphi(\theta; \hat{\theta}_t, VC_t^* + W_t) d\theta \right] \times IG\left(\frac{n_t}{2}, \frac{n_t S_t}{2}\right) dV \\ &= \int_0^\infty \varphi(TVI_t; Z_t' \hat{\theta}_t, Z_t' (VC_t^* + W_t) Z_t') + V \times IG\left(\frac{n_t}{2}, \frac{n_t S_t}{2}\right) dV \\ &= t_{n_t}(TVI_{t+1}; \widehat{TVI}_{t+1}, Q_{t+1}) \end{aligned} \quad (\text{B.18})$$



### B.3 Dynamic Model Averaging

The choices of different predictors and different time-variation in coefficients crucially affect the predictive density of the individual models. We conduct the Dynamic Model Averaging following Koop and Korobilis (2012). Denote  $M_j^t$  as a certain selection of predictors from the  $m$  variables at  $t$ , and  $\delta_k^t$  as a certain choice from the possible set  $\{\delta_1, \delta_2, \dots, \delta_d\}$  at time  $t$ . Given model  $M_j^t$  and  $\delta = \delta_k^t$ , we rewrite the estimate of  $TVI_{t+1}$  as:

$$\widehat{TVI}_{t,j}^k = \mathbb{E}(TVI_{t+1} \mid M_j^t, \delta_k^t, D_t) = Z_t' \hat{\theta}_t \mid M_j^t, \delta_k^t, D_t \quad (\text{B.19})$$

For the initial weight of each individual model, we set a diffuse conditional prior  $P(M_j^0 \mid \delta_k^0, D_0) = 1/(2^m - 1) \forall i$ . The posterior probabilities for model updating equation are obtained through Bayes' rule:

$$P(M_j^t \mid \delta_k^t, D_t) = \frac{f(TVI_t \mid M_j^t, \delta_k^t, D_{t-1}) P(M_j^t \mid \delta_k^t, D_{t-1})}{\sum_m f(TVI_t \mid M_j^t, \delta_k^t, D_{t-1}) P(M_j^t \mid \delta_k^t, D_{t-1})} \quad (\text{B.20})$$

where the prediction equation is:

$$P(M_j^t \mid \delta_k^t, D_{t-1}) = \frac{P(M_j^{t-1} \mid \delta_k^{t-1}, D_{t-1})^\alpha}{\sum_m P(M_j^{t-1} \mid \delta_k^{t-1}, D_{t-1})^\alpha} \quad (\text{B.21})$$

The conditional density is:

$$f(TVI_t \mid M_j, \delta_k, D_{t-1}) \sim \frac{1}{\sqrt{Q_{t,j}^k}} t_{n_{t-1}} \left( \frac{TVI_t - \widehat{TVI}_{t,j}^k}{\sqrt{Q_{t,j}^k}} \right) \quad (\text{B.22})$$

where  $t_{n_{t-1}}$  is the density of a student  $t$  distribution with degrees of freedom  $n_{t-1}$ , and  $Q_{t,j}^k$  is the variance of the predictive distribution of model  $M_j$  given time variation in coefficients  $\delta_k$ . Average all the possible models, the return

prediction given  $\delta = \delta_k$  is:

$$\widehat{TVI}_t^k = \sum_{j=1}^{2^m-1} P(M_j^t | \delta_k^t, D_t) \widehat{TVI}_{t,j}^k \quad (\text{B.23})$$

We also perform Bayesian model averaging over different values of time-variation in coefficients  $\delta$ . A diffuse prior probability of  $1/d$  is assigned to each  $\delta$ . Then the posterior probability of a certain  $\delta$  at time  $t$  is given by:

$$P(\delta_k^t | D_t) = \frac{f(TVI_t | \delta_k^t, D_{t-1}) P(\delta_k^t | D_{t-1})}{\sum_{\delta} f(TVI_t | \delta_k^t, D_{t-1}) P(\delta_k^t | D_{t-1})} \quad (\text{B.24})$$

where

$$P(\delta_k^t | D_t) = \frac{P(\delta_k^t | D_{t-1})^\alpha}{\sum_d P(\delta_k^t | D_{t-1})^\alpha} \quad (\text{B.25})$$

and we can find the time-variation in coefficients supported by the data.

Besides, the posterior probability of a certain model given a choice of predictor and  $\delta$  is denoted as:

$$P(M_j^t, \delta_k^t | D_t) = P(M_j^t | \delta_k^t, D_t) P(\delta_k^t | D_t) \quad (\text{B.26})$$

Finally, the unconditional prediction of integration is:

$$\widehat{TVI}_{t+1} = \sum_{k=1}^d P(\delta_k^t | D_t) \widehat{TVI}_{t+1}^k \quad (\text{B.27})$$

TABLE B.1: MSCI Data Description and DataStream Mnemonic

Country	Index identification	DataStream mnemonic
Australia	MSCI Australia U\$ - Price Index	MSAUST\$
Austria	MSCI Austria U\$ - Price Index	MSASTR\$
Belguim	MSCI Belgium U\$ - Price Index	MSBELG\$
Canada	MSCI Canada U\$ - Price Index	MSCNDA\$
Denmark	MSCI Denmark U\$ - Price Index	MSDNMK\$
France	MSCI France U\$ - Price Index	MSFRNC\$
Germany	MSCI Germany U\$ - Price Index	MSGERM\$
Hong Kong	MSCI Hong Kong U\$ - Price Index	MSHGKG\$
Italy	MSCI Italy U\$ - Price Index	MSITAL\$
Japan	MSCI Japan U\$ - Price Index	MSJPAN\$
Netherlands	MSCI Netherlands U\$ - Price Index	MSNETH\$
Norway	MSCI Norway U\$ - Price Index	MSNWAY\$
Singapore	MSCI Singapore U\$ - Price Index	MSSING\$
Spain	MSCI Spain U\$ - Price Index	MSSPAN\$
Sweden	MSCI Sweden U\$ - Price Index	MSSWDN\$
Switzerland	MSCI Switzerland U\$ - Price Index	MSSWIT\$
United Kingdom	MSCI UK U\$ - Price Index	MSUTDK\$
United States	MSCI USA U\$ - Price Index	MSUSAM\$

*Notes:* Country-specific MSCI price index and its DataStream mnemonic. All index values are converted in to the U.S. dollar. For each country, data starts from 31-Dec-1969 to 11-Jan-2017. 2445 weekly observations are obtained.

TABLE B.2: Trend and Break Tests of H-P Filtered Financial Integration

	Trend Test		Break Test			
	<i>Trend</i>	<i>t test</i>	$W_{RQF}$	$T_{break}$	<i>Before</i>	<i>After</i>
Australia	0.10%	1.09	1.54	1998Q2	0.30	0.46
Austria	0.11%	0.71	1.59	1985Q4	0.28	0.34
Belgium	0.07%	0.70	1.41	2002Q1	0.14	0.28
Canada	0.08%	1.87*	1.37	2007Q4	0.34	0.48
Denmark	0.13%	1.81*	0.43	2000Q4	0.26	0.34
France	0.26%	2.22**	1.05	2000Q1	0.32	0.47
Germany	0.13%	1.53	2.29	1998Q2	0.32	0.49
Hong Kong	0.25%	2.33**	8.22***	1986Q2	0.57	0.73
Italy	0.13%	0.90	1.12	1998Q3	0.36	0.58
Japan	0.11%	1.27	1.67	2007Q1	0.15	0.28
Netherlands	0.15%	1.54	3.45**	2007Q4	0.37	0.56
Norway	0.07%	0.71	1.19	1998Q1	0.40	0.56
Singapore	0.23%	2.35**	3.93**	1984Q3	0.36	0.56
Spain	0.17%	2.00**	2.58*	2008Q3	0.50	0.65
Sweden	0.10%	0.85	1.87	1997Q1	0.31	0.47
Switzerland	0.29%	2.38**	1.06	2000Q2	0.41	0.53
United Kingdom	0.18%	1.45	0.60	2000Q3	0.35	0.49
United States	0.08%	1.46	1.84	2007Q4	0.44	0.57

Notes: See detailed notes in Table 3.3 and 3.4.

TABLE B.3: Test for Differences in Means Between Integration Derived from Constant Parameters and Our Integration Measure

	<i>Test stat.</i>		<i>Test stat.</i>
Australia	-38.43***	Japan	-20.82***
Austria	-33.18***	Netherlands	-39.64***
Belgium	-25.91***	Norway	-43.65***
Canada	-41.81***	Singapore	-40.16***
Denmark	-29.13***	Spain	-51.31***
France	-27.82***	Sweden	-36.54***
Germany	-40.38***	Switzerland	-37.14***
Hong Kong	-60.48***	United Kingdom	-31.81***
Italy	-37.36***	United States	-48.46***

*Notes:* This table reports the  $t$  statistics with Newey-West correction for a one-sided test, based on the null hypothesis that the mean of the integration derived from constant parameters is higher than our integration measure for the corresponding country. The 1%(\*), 5%(\*\*) and 10% (\*\*\*) critical values are 2.33, 1.65 and 1.28 respectively.

TABLE B.4: Test for Differences in Means of Integration Before and After Breaks

	<i>Test stat.</i>		<i>Test stat.</i>
Australia	-11.59***	Japan	-5.56***
Austria	-2.18**	Netherlands	-9.83***
Belgium	-11.36***	Norway	-4.41***
Canada	-7.94***	Singapore	-8.69***
Denmark	-2.90***	Spain	-7.88***
France	-4.62***	Sweden	-9.45***
Germany	-9.20***	Switzerland	-3.89***
Hong Kong	-6.52***	United Kingdom	-4.61***
Italy	-13.88***	United States	-6.41***

*Notes:* This table reports the  $t$  statistics with Newey-West correction for a one-sided test based on the null hypothesis that the mean of the integration before the breaks is higher than that after the breaks. The 1%(\*), 5%(\*\*) and 10% (\*\*\*) critical values are 2.33, 1.65 and 1.28 respectively.

TABLE B.5: Pair-Wise Granger Causality Test Between Integration and VIX

Country	Null Hypotheses	F stat	Prob
Australia	Integration does not Granger cause VIX	0.04	0.84
	VIX does not Granger cause integration	4.55	<b>0.01***</b>
Austria	Integration does not Granger cause VIX	0.03	0.87
	VIX does not Granger cause integration	3.82	<b>0.03**</b>
Belgium	Integration does not Granger cause VIX	0.86	0.36
	VIX does not Granger cause integration	2.83	<b>0.06*</b>
Canada	Integration does not Granger cause VIX	0.27	0.61
	VIX does not Granger cause integration	5.31	<b>0.01***</b>
Denmark	Integration does not Granger cause VIX	1.27	0.26
	VIX does not Granger cause integration	5.35	<b>0.02**</b>
France	Integration does not Granger cause VIX	1.65	0.20
	VIX does not Granger cause integration	2.94	<b>0.01***</b>
Germany	Integration does not Granger cause VIX	0.07	0.79
	VIX does not Granger cause integration	3.43	<b>0.00***</b>
Hong Kong	Integration does not Granger cause VIX	1.56	0.20
	VIX does not Granger cause integration	0.53	0.72
Italy	Integration does not Granger cause VIX	0.18	0.67
	VIX does not Granger cause integration	4.21	<b>0.02**</b>
Japan	Integration does not Granger cause VIX	0.10	0.75
	VIX does not Granger cause integration	0.16	0.69
Netherlands	Integration does not Granger cause VIX	0.04	0.84
	VIX does not Granger cause integration	4.22	<b>0.02**</b>
Norway	Integration does not Granger cause VIX	0.22	0.64
	VIX does not Granger cause integration	4.79	<b>0.01***</b>
Singapore	Integration does not Granger cause VIX	0.07	0.80
	VIX does not Granger cause integration	1.62	0.20
Spain	Integration does not Granger cause VIX	0.31	0.58
	VIX does not Granger cause integration	3.34	<b>0.04**</b>
Sweden	Integration does not Granger cause VIX	0.03	0.86
	VIX does not Granger cause integration	3.81	<b>0.03**</b>
Switzerland	Integration does not Granger cause VIX	0.25	0.62
	VIX does not Granger cause integration	5.42	<b>0.01***</b>
United Kingdom	Integration does not Granger cause VIX	0.17	0.68
	VIX does not Granger cause integration	4.78	<b>0.03**</b>
United States	Integration does not Granger cause VIX	0.17	0.68
	VIX does not Granger cause integration	3.44	<b>0.04**</b>

Notes: This table reports the  $F$  statistics and  $p$  values for the Granger causality test between financial integration and VIX for different countries. The order of the Granger causality test is optimally selected by the AIC and BIC criterion.

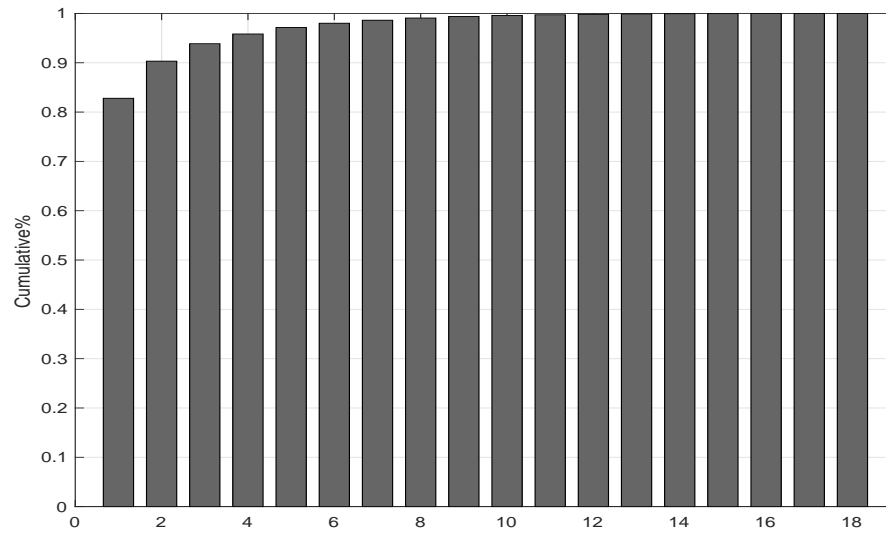
TABLE B.6: Average Inclusion Probabilities of Different Predictors for the Integration Derived from Constant Loadings and Risk

	VIX	FDI	Growth	NBER	Trade
Australia	0.16	0.24	0.01	0.01	0.02
Austria	0.03	0.02	0.02	0.02	0.13
Belgium	0.18	0.05	0.02	0.02	0.21
Canada	0.13	0.06	0.01	0.02	0.20
Denmark	0.18	0.02	0.01	0.01	0.13
France	0.13	0.07	0.01	0.01	0.03
Germany	0.19	0.04	0.04	0.01	0.10
Hong Kong	0.04	0.01	0.01	0.37	0.07
Italy	0.19	0.06	0.23	0.09	0.05
Japan	0.06	0.06	0.01	0.03	0.11
Netherlands	0.13	0.04	0.04	0.03	0.06
Norway	0.20	0.26	0.01	0.01	0.07
Singapore	0.09	0.01	0.01	0.04	0.16
Spain	0.14	0.12	0.01	0.13	0.07
Sweden	0.12	0.20	0.19	0.01	0.07
Switzerland	0.09	0.02	0.01	0.02	0.12
United Kingdom	0.05	0.07	0.01	0.20	0.03
United States	0.18	0.08	0.01	0.02	0.12
G7	0.13	0.06	0.05	0.05	0.09
Overall average	0.13	0.08	0.04	0.06	0.10

*Notes:* This table presents the average inclusion probabilities of different predictors for the integration derived from constant loadings and risk over the corresponding sample periods. The description of the predictors is as follows: FDI refers to investment openness, Growth refers to real GDP per capita, NBER refers to NBER recession dummy, Trade refers to trade openness and VIX refers to the Chicago Board Options Exchange (CBOE) Volatility Index. We also summarize the average inclusion probabilities for G7 countries and for all the countries we consider.

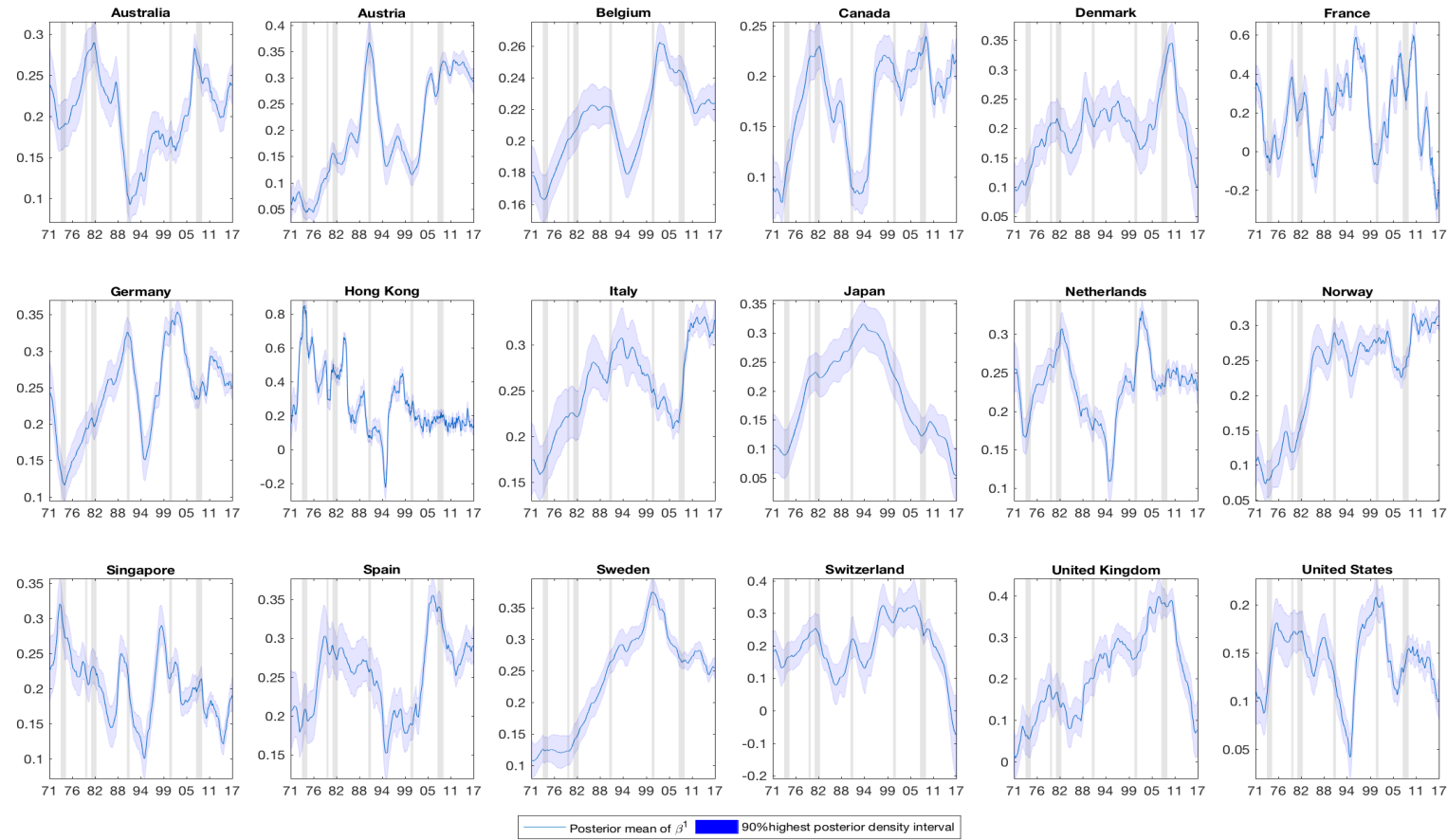


FIGURE B.1: Average Cumulative Percentage of Variance Explained by the Out-of-sample Principal Components



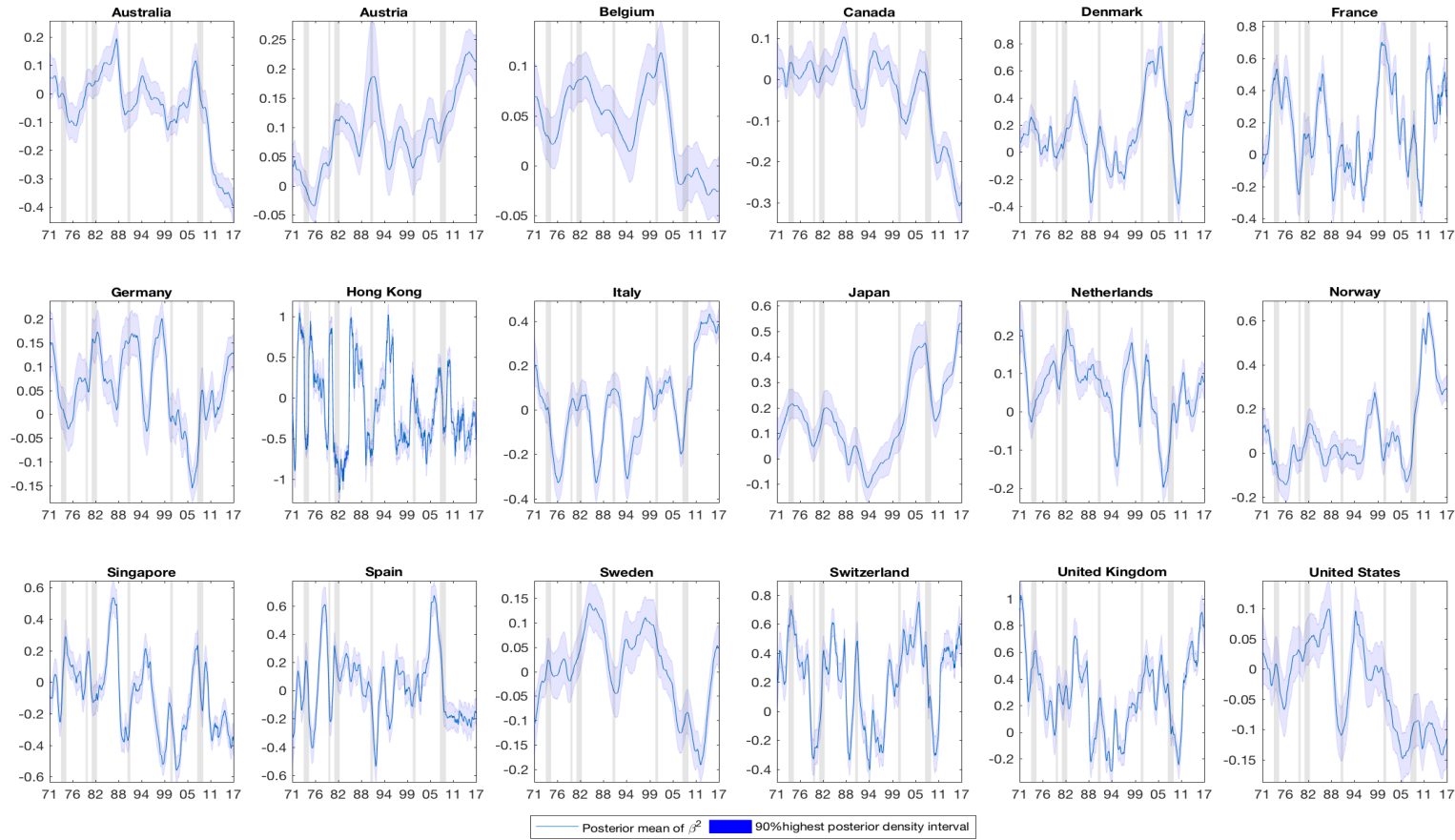
*Notes:* The figure shows the average cumulative percentage of variance explained by all the 18 out-of-sample principal components.

FIGURE B.2: Factor Loading on The First Global Factor



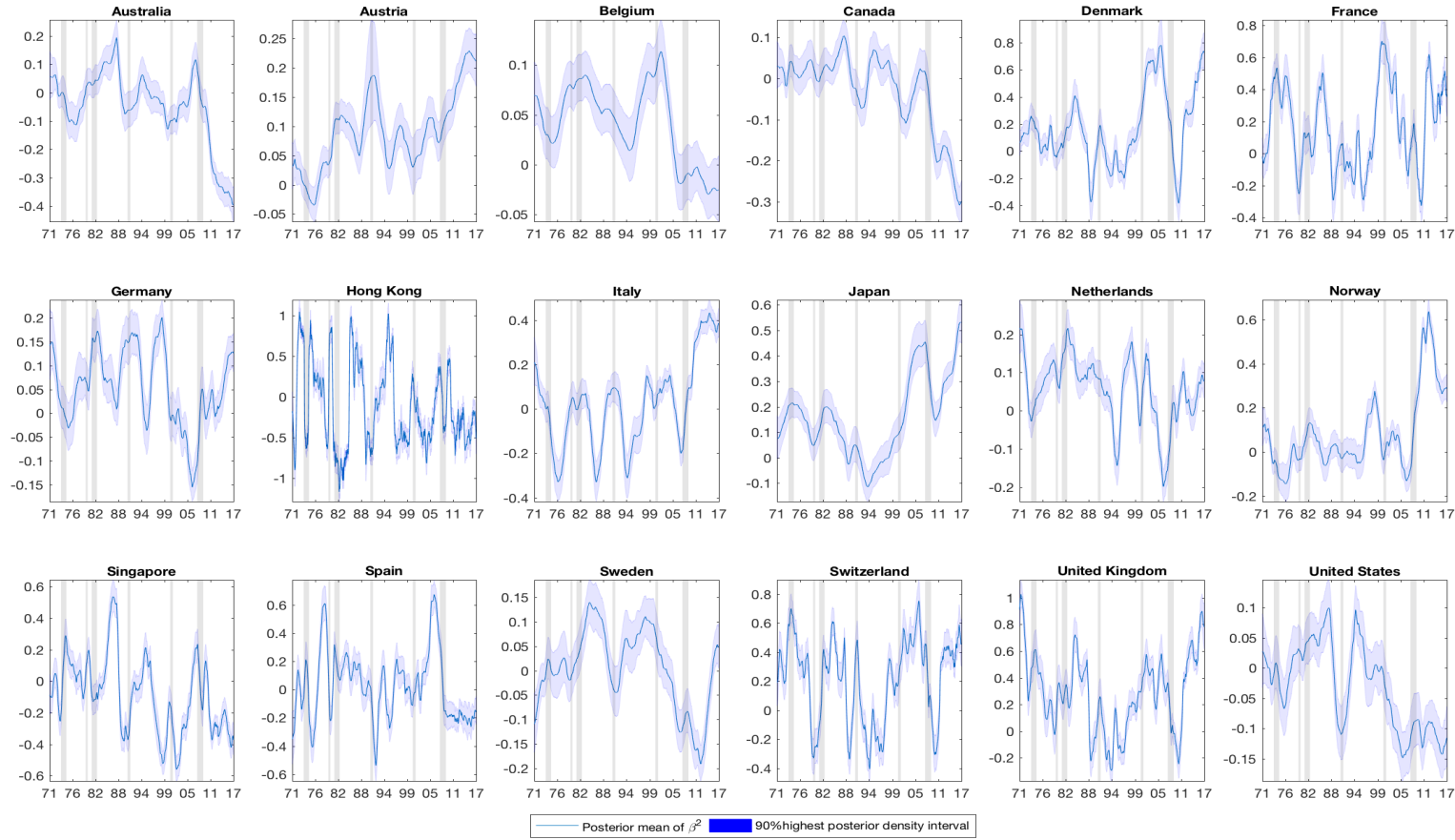
Notes: This figure shows the factor loading on the first global factor  $\beta_{i,t}^1$  in Equation (3.1) for different economies. The shaded area is the NBER recession dates.

FIGURE B.3: Factor Loading on The Second Global Factor



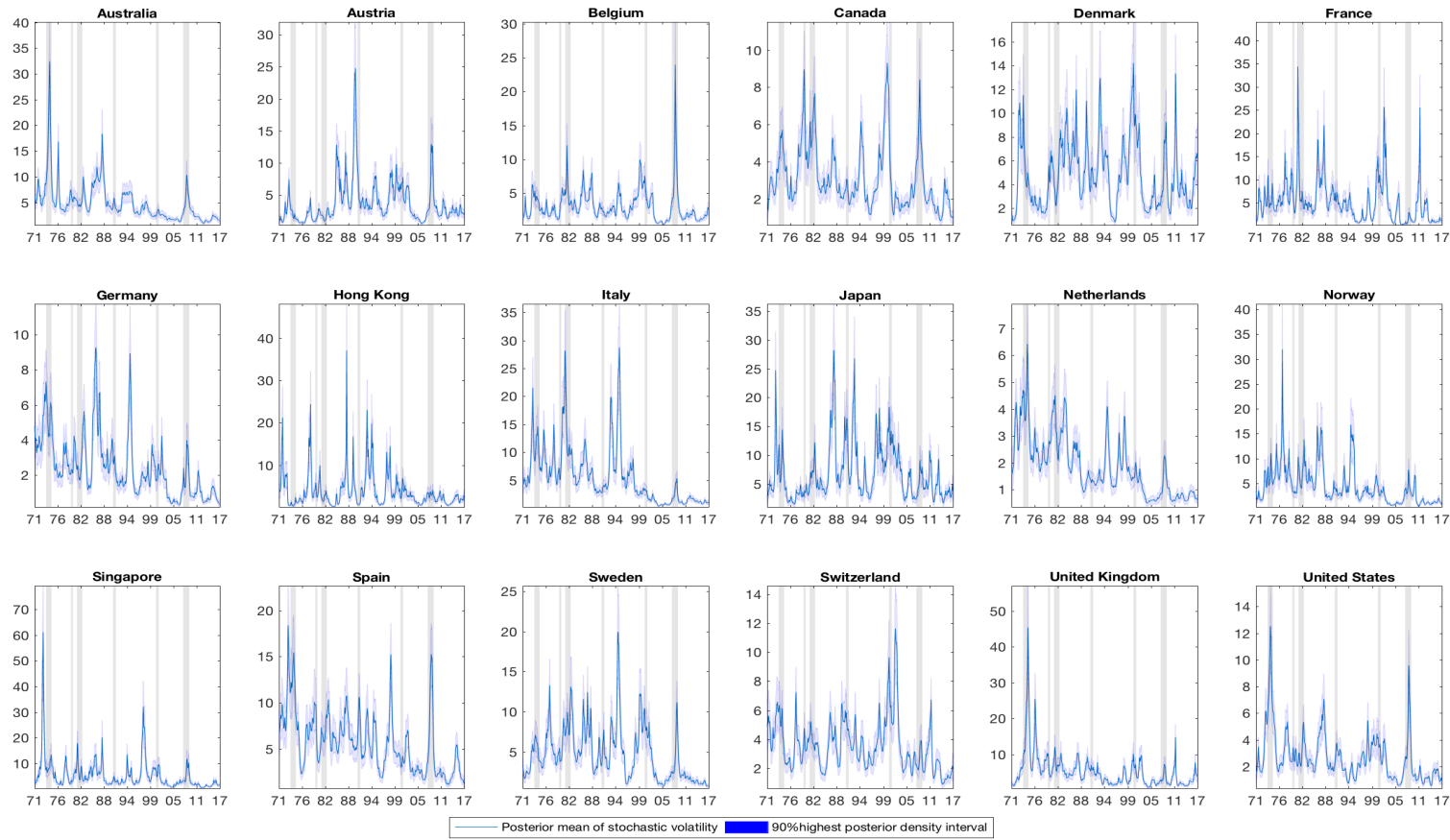
Notes: This figure shows the factor loading on the second global factor  $\beta^2_{i,t}$  in Equation (3.1) for different economies. The shaded area is the NBER recession dates.

FIGURE B.4: Country-specific Factor



Notes: This figure shows the country-specific factor  $\mu_{i,t}$  in Equation (3.1) for different economies. The shaded area is the NBER recession dates.

FIGURE B.5: Stochastic Volatility



Notes: This figure shows the stochastic volatility  $h_{i,t}$  in Equation (3.1) for different economies. The shaded area is the NBER recession dates.

## Appendix C

### Appendix of Chapter 4

This appendix contains more details of Chapter 4. Section C.1 presents the method to optimize the parameters in smooth transition VAR. Section C.2 provides the test we employ to detect the non-linear dynamics for our framework. We also show additional results for robustness checks and the estimation of smooth transition VAR.

#### C.1 Nonlinear Least Squares Estimation

After selecting the financial uncertainty as our transition variable, the STVAR is estimated using nonlinear least squares (NLS), the traditional derivative-based optimization techniques. The model in Equation (4.2) includes the parameters  $\theta = \{\mathbf{B}, \tau, c\}$ , where  $\mathbf{B} = (B_1(L), B_2(L))$ . The NLS estimators are obtained by solving the following optimization problem:

$$\hat{\theta} = \arg \min_{\theta} Q_T(\theta) = \arg \min_{\theta} \sum_{t=1}^T (X_t - \Psi_t' \mathbf{B} X_{t-1})' (X_t - \Psi_t' \mathbf{B} X_{t-1}) \quad (\text{C.1})$$

In practice, it may be difficult to find the optimum for the objective function  $Q_T(\theta)$  as the convergence to the optimum may be slow and some local minimums instead of the global ones could be picked up by the algorithm,

especially when the function is flat in many directions. Therefore, a suitable starting-value of  $\theta$  for the nonlinear optimization is crucial for the estimation.

Here we adopt the “grid search” algorithm to find the optimum. It solves the optimization problem by converting the nonlinear model into simple linear regressions using a discrete grid. Specifically, a discrete grid for parameters  $\tau$  and  $c$  is constructed.<sup>1</sup> We then estimate the parameters in  $\mathbf{B}$  conditional on each pair of  $\tau$  and  $c$  in the grid as the model is linear. The pair of  $\tau$  and  $c$  producing the smallest residuals sum of squares and the corresponding estimated  $\mathbf{B}$  are chosen to be the starting-values for the nonlinear optimization.

Therefore, using the “grid search” algorithm, we measure the conditional minimizer of the objective function  $Q_T(\theta)$  by solving the first-order condition equations for a fixed  $\Psi_t$ :

$$\sum_{t=1}^T X_{t-1}(X_t - \Psi_t' \mathbf{B}' X_{t-1})' \Psi_t' = 0 \quad (\text{C.2})$$

which can be rewritten as:

$$\sum_{t=1}^T X_{t-1} X_t' \Psi_t' = \sum_{t=1}^T X_{t-1} X_{t-1}' \mathbf{B} \Psi_t \Psi_t' \quad (\text{C.3})$$

Consequently, the closed form of the NLS estimator of  $\mathbf{B}$  conditional on  $\tau$  and  $c$  is:

$$\text{vec}(\hat{\mathbf{B}}) = \left[ T^{-1} \sum_{t=1}^T (\Psi_t \Psi_t' \otimes (X_{t-1} X_{t-1}')) \right]^{-1} \left[ T^{-1} \sum_{t=1}^T \text{vec}(X_{t-1} X_t' \Psi_t') \right] \quad (\text{C.4})$$

where  $\text{vec}(\cdot)$  is the vectorization operator.

---

<sup>1</sup>The upper bound of  $\tau$  should be a value large enough to close to the threshold effect, but not too large, given that likelihood becomes flat over  $\tau$ . Generally, the upper bound for  $\tau$  depends on the observations of the transition variable. The larger the observations of  $z$  become, the lower the value of  $\tau$ . This is because you need to have enough observations of  $z$  around the threshold  $c$  in order to obtain an accurate estimate of  $\tau$ . Hence, when  $z$  has more extreme realizations, the support of  $c$  becomes larger, the slope parameter  $\tau$  has to be small enough to compensate for that.

Therefore, following Teräsvirta and Yang (2014b), we obtain the conditional NLS estimators given  $\tau$  and  $c$ :

$$\text{vec}(\hat{\mathbf{B}}) = (\mathbf{M}\mathbf{M}')^{-1}\mathbf{M}'\text{vec}(X'_t) \quad (\text{C.5})$$

$$\hat{\Omega} = T^{-1}\hat{\mathbf{E}}'\hat{\mathbf{E}} \quad (\text{C.6})$$

where  $M = (\Upsilon_1, \Upsilon_2, \dots, \Upsilon_T)'$ ,  $\Upsilon_t = \Psi_t \otimes (X_{t-1})$ ,  $\hat{\mathbf{E}} = (\hat{u}_1, \hat{u}_2, \dots, \hat{u}_T)'$ , and  $\hat{u}_t = X_t - \Psi_t'\hat{\mathbf{B}}X_{t-1}$  is a vector of residuals.<sup>2</sup>

## C.2 Non-linearity Tests

We employ the test acknowledged by Teräsvirta and Yang (2014a) to detect the non-linear dynamics for our model. Their framework is suitable for our analysis as it tests the linearity of a VAR versus a smooth transition VAR with a single transition variable.

Consider the following two-regime logistic STVAR model:

$$\mathbf{X}_t = \Theta'_0 \mathbf{Y}_t + \Theta'_1 \mathbf{Y}_t z_t + \varepsilon_t \quad (\text{C.7})$$

where  $\mathbf{X}_t$  is the  $(p \times 1)$  vector of dependent variables,  $\mathbf{Y}_t = [\mathbf{X}_{t-1}, \dots, \mathbf{X}_{t-k}, \alpha]$  is the  $((k \times p + q) \times 1)$  vector of explanatory variables including constants  $\alpha$ ,  $z_t$  is the transition variable,  $p$  is the number of endogenous variables,  $q$  is the number of exogenous variables and  $k$  denotes the number of lags. Under the null hypothesis of Teräsvirta and Yang (2014a) test,  $\Theta_1 = 0$ .

The procedures to perform Teräsvirta and Yang (2014a) test are as follows:

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<sup>2</sup> Teräsvirta and Yang (2014b) prove that the probability limit of the average NLS function has a unique global optimum at the true parameters, and the NLS estimator is consistent and asymptotic normal.



1. Estimate the restricted model by regressing  $\mathbf{X}_t$  on  $\mathbf{Y}_t$ . Collect the residuals  $\tilde{\mathbf{E}}$  and calculate residual sum of squares  $\mathbf{RSS}_0 = \tilde{\mathbf{E}}' \tilde{\mathbf{E}}$ .
2. Estimate an auxiliary regression  $\tilde{\mathbf{E}}$  on  $(\mathbf{Y}_t, \mathbf{Z}_t)$  where  $\mathbf{Z}_t = [\mathbf{X}_t' z_t]$ . Collect the residuals  $\tilde{\tilde{\mathbf{E}}}$  and calculate residual sum of squares  $\mathbf{RSS}_1 = \tilde{\tilde{\mathbf{E}}}' \tilde{\tilde{\mathbf{E}}}$ .
3. Compute the test statistic

$$\begin{aligned}
 LM &= T(tr(\mathbf{RSS}_0^{-1}(\mathbf{RSS}_0 - \mathbf{RSS}_1))) \\
 &= T(p - tr(\mathbf{RSS}_0^{-1} \mathbf{RSS}_1))
 \end{aligned} \tag{C.8}$$

The test statistics follows  $\chi^2$  with  $p \times (kp + q)$  degrees of freedom under the null hypothesis.

4. According to Teräsvirta and Yang (2014a), the LM-type test derived in the previous step may suffer from positive size distortion in small samples, due to the problem that empirical size of the LM-test could exceed the true asymptotic size. Following Teräsvirta and Yang (2014a), we then apply the rescaled LM test statistics:

$$F = \frac{(pT - k)}{G \times pT} LM$$

where  $G$  denotes the number of restrictions and this rescaled test statistics follows an  $F(G, pT - k)$  distribution.

We uncover that the test statistics generated from step 3 is 415.94 and the rescaled test statistics from step 4 is 207.91, both of which have p-values close to 0. We strongly reject the null hypothesis of linearity and confirm the specification of a smooth transition VAR.

### C.3 Estimation of the Smooth Transition VAR with State-Dependent Variance

The smooth transition VAR as in Auerbach and Gorodnichenko (2012) is estimated using the maximum likelihood, which is represented as follows:

$$\log L = \text{const} - \frac{1}{2} \sum_{t=1}^T \log |\Xi_t| - \frac{1}{2} \sum_{t=1}^T u_t' \Xi_t^{-1} u_t \quad (\text{C.9})$$

where  $u_t = X_t - (1 - F(z_{t-1}))\Pi_{LU}(L)X_{t-1} - F(z_{t-1})\Pi_{HU}(L)X_{t-1}$ . Following Auerbach and Gorodnichenko (2012), we aim to estimate the parameters  $\Psi = \{\tau, \Xi_{LU}, \Xi_{HU}, \Pi_{LU}(L), \Pi_{HU}(L)\}$  in the non-linear VAR.

We notice that the model is linear conditional on  $\Psi = \{\tau, \Xi_{LU}, \Xi_{HU}\}$ . Then given a prior for  $\Psi = \{\tau, \Xi_{LU}, \Xi_{HU}\}$ , the coefficients can be measured by minimizing  $\frac{1}{2} \sum_{t=1}^T u_t' \Xi_t^{-1} u_t$ . Denote  $W_t = [F(z_{t-1})X_{t-1}, (1 - F(z_{t-1}))X_{t-1}, \dots, F(z_{t-1})X_{t-p}, (1 - F(z_{t-1}))X_{t-p}]$  and  $\Pi = [\Pi_{LU} \quad \Pi_{HU}]$ . The objective function is:

$$\frac{1}{2} \sum_{t=1}^T (X_t - \Pi W_t')' \Xi_t^{-1} (X_t - \Pi W_t') \quad (\text{C.10})$$

The first order condition with respect of  $\Pi$  can be showed as:

$$\text{vec} \Pi' = \left( \sum_{t=1}^T [\Xi_t \otimes W_t W_t'] \right)^{-1} \text{vec} \left( \sum_{t=1}^T W_t' X_t \Xi_t^{-1} \right) \quad (\text{C.11})$$

The procedure above iterates over different values of  $\Psi = \{\tau, \Xi_{LU}, \Xi_{HU}\}$  and consequently we can obtain the optimum  $\Xi$  and likelihood.<sup>3</sup> To make sure that  $\Xi_{LU}$  and  $\Xi_{HU}$  are positive definite, we alternately use  $\Psi = \{\tau, \text{chol}(\Xi_{LU}), \text{chol}(\Xi_{HU}), \Pi_{LU}(L), \Pi_{HU}(L)\}$ , where *chol* represents the cholesky decomposition. Moreover, to construct the confidence interval and impulse response functions of

<sup>3</sup>Note that several optima could be achieved therefore one should try different values prior for  $\Psi = \{\tau, \Xi_{LU}, \Xi_{HU}\}$ .

the non-linear VAR, we adopt the Hastings-Metropolis algorithm proposed by Chernozhukov and Hong (2003). Specifically, the procedure measures chains of length  $N$  following steps below:

**Step 1:** Draw a candidate vector  $\Theta^{(n)} = \Psi^{(n)} + \psi^{(n)}$  at the state  $n + 1$ , where  $\Psi^{(n)}$  is the vector for the current state,  $\psi^{(n)}$  is a vector of shocks drawn from  $N \sim (0, \Omega_\Psi)$  and  $\Omega_\Psi$  is diagonal.

**Step 2:** Set the  $n + 1$  state  $\Psi^{(n+1)} = \Theta^{(n+1)}$  with probability  $\min\{1, \frac{L(\Theta^{(n)})}{L(\Psi^{(n)})}\}$  or  $\Psi^{(n)}$  otherwise, where  $L()$  is the objective function.

Based on the Taylor approximation of the model discussed above, the prior of  $\Psi^{(0)}$  is calculated by regressing  $X_t$  on lags of  $X_t$ ,  $X_t z_t$  and  $X_t z_t^2$ . We employ the residuals from this model to form the time-varying variance-covariance matrix of the VAR,  $\Xi_{LU}$  and  $\Xi_{HU}$ . Consequently, we can obtain the starting values for the lag polynomials  $\{\Pi_{LU}(L), \Pi_{HU}(L)\}$  via equation (C.11).

The initial value for the diagonal matrix  $\Omega_\Psi$  is set to be one percent of the parameters values and then adjusted to generate an 0.3 acceptance rate of candidate draws, suggested by Canova (2007). We employ 100,000 draws for the model and retain the last 20,000 draws for estimation and inference.

Chernozhukov and Hong (2003) show that  $\hat{\Psi} = \frac{1}{N} \sum_{n=1}^N \Psi^{(n)}$  is a consistent estimator of  $\Psi$  under standard regularity assumptions. However, as shown in Auerbach and Gorodnichenko (2012), when applying the Chernozhukov and Hong (2003) algorithm, it could be problematic for the estimation of impulse responses using the standardization of the size of the shock.<sup>4</sup> Instead, we solve the issue based on the discussion in Hamilton (1994). Specifically, we draw the lag polynomials  $\{\Pi_{LU}(L), \Pi_{HU}(L)\}$  from the MCMC chain  $\{\Psi^{(n)}\}^N$  and the covariance matrix of residuals in regime  $s$  ( $s$  can either be low uncertainty or

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<sup>4</sup>Please find the demonstration of the impulse response issue from the appendix of Auerbach and Gorodnichenko (2012).

high uncertainty) is drawn from  $N(\text{vec}(\Xi_s), O_s)$ , where

$$O_s = 2[(D_n' D_n)^{-1} D_n] \text{var}(\text{vec}(\Xi_s)) \otimes \text{var}(\text{vec}(\Xi_s)) [(D_n' D_n)^{-1} D_n]' \quad (\text{C.12})$$

Here  $D_n$  is a duplication matrix and  $\text{Var}(\text{vec}(\Xi_j))$  is obtained from  $\{\Psi^{(n)}\}^N$ .

## C.4 Factors For the FAVAR Approach

Denote  $\mathbf{X}_t = (X_{1t}, \dots, X_{nt})'$  as a vector of  $n$  macroeconomic and financial time series, where  $X_{it}$  is a single time series transformed to be stationary. The dynamic factor model states that each of the  $n$  series can be driven by  $r$  unobserved factors  $\mathbf{F}_t$  and an idiosyncratic error term  $\mathbf{e}_t$ :

$$\mathbf{X}_t = \Lambda \mathbf{F}_t + \mathbf{e}_t \quad (\text{C.13})$$

where  $\Lambda$  is the  $n \times r$  matrix of factor loadings and  $\mathbf{e}_t = (e_{1t}, \dots, e_{nt})'$ .

We assume the unobserved factors to follow a linear and stationary vector autoregression process:

$$\Phi(\mathbf{L}) \mathbf{F}_t = \eta_t \quad (\text{C.14})$$

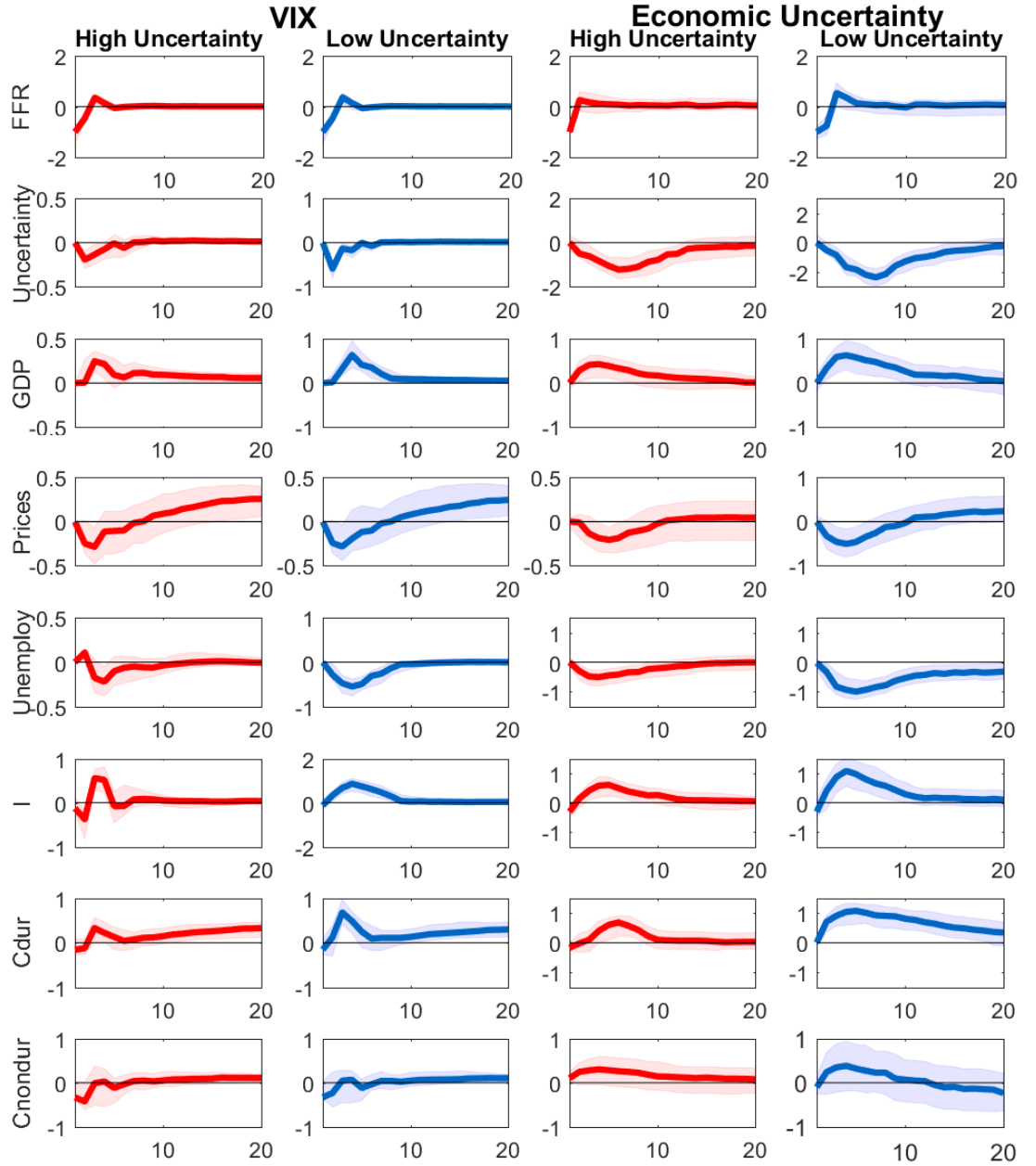
where  $\Phi(\mathbf{L})$  is a  $r \times r$  matrix of lag polynomials. When  $n$  is large, under the assumption that there is multiple factors, Stock and Watson (2002) propose that principal components are consistent estimators of  $\mathbf{F}_t$ . We therefore extract the first principal of component from the McCracken and Ng (2016) dataset and include it in the STVAR.

TABLE C.1: Data Sources and Transformation

No.	Name	Source and ID	tcode
1	GDP	FRED (GDPC96)	5
2	Prices	FRED (GDPDEF)	5
3	Unemployment Rate	FRED (UNRATE)	5
4	investment	FRED (GDPIC96)	6
5	C_durable	FRED (DDURRG3M086SBEA)	6
6	C_nondurable	FRED (DNDGRG3M086SBEA)	6
7	Mprime-TB3MS	FRED (MPRIME-TB3MS)	1
8	BAA-AAA	FRED (BAA-AAA)	1
9	S&P 500	DATASTREAM (S&PCOMP)	5
10	Volatility S&P	See No.10	5
11	LOANINV	FRED (LOANINV)	6
12	REALLN	FRED (REALLN)	6

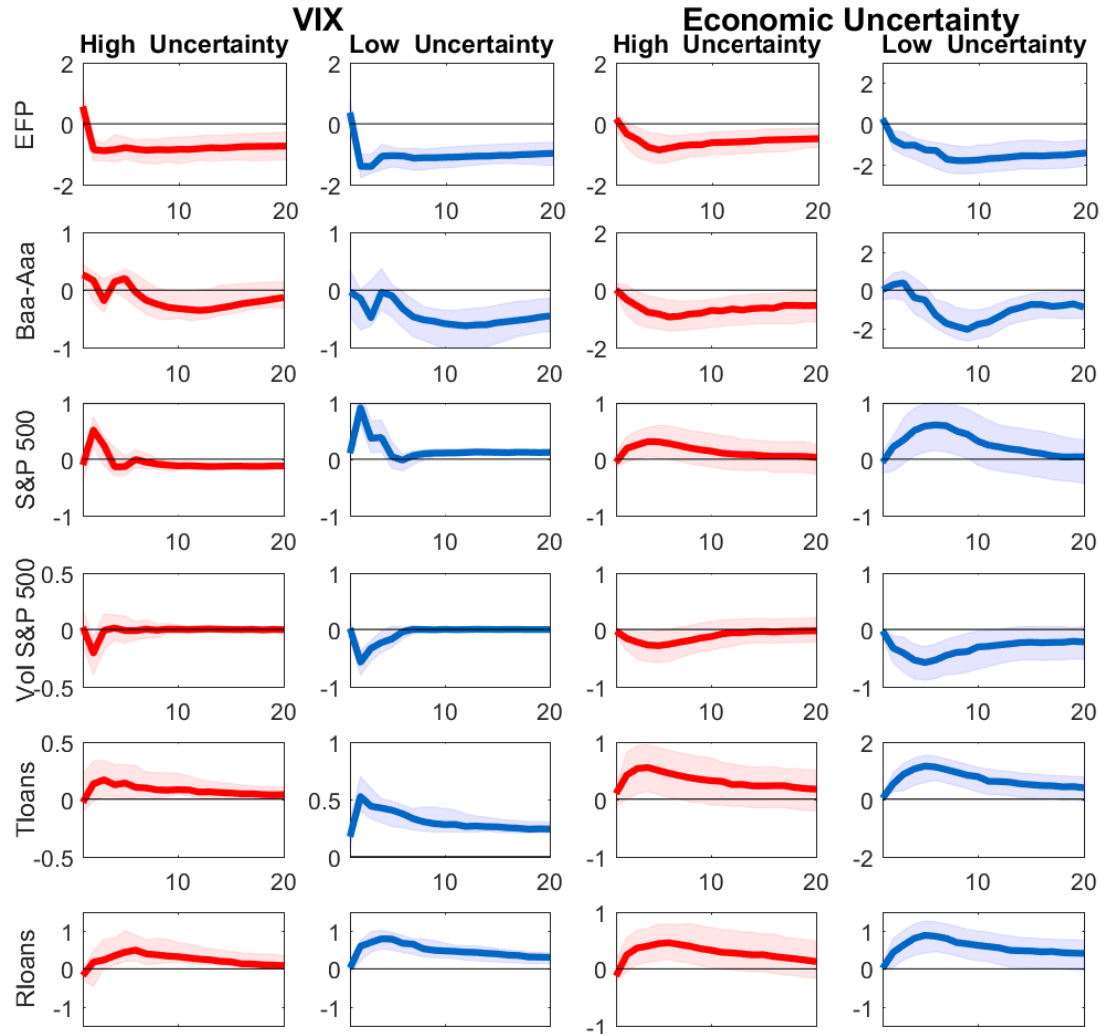
*Notes:* This table presents the data sources and transformation. The data set is at quarterly frequency, with 228 observations. The *tcode* column represents the following transformation for the actual series  $X_{it}$ : (1) no transformation; (2)  $\Delta X_{it}$ ; (3)  $\Delta^2 X_{it}$ ; (4)  $\log(X_{it})$ ; (5)  $\Delta \log(X_{it})$ ; (6)  $\Delta^2 \log(X_{it})$

FIGURE C.1: Alternative Uncertainty Indicators: State-dependent Responses of Macroeconomic Variables to a Expansionary Monetary Policy Shock.



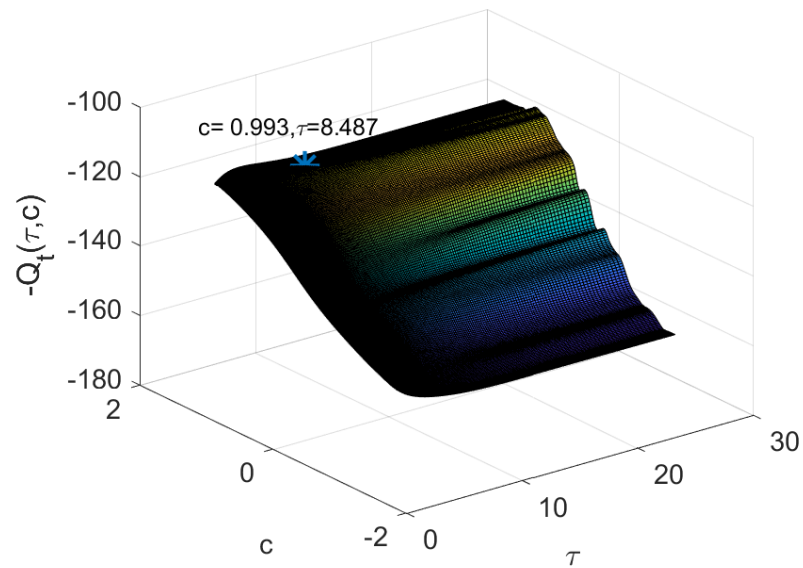
Notes: The first two columns show the state-dependent responses using the VIX index as the uncertainty indicator and the last two columns present the state-dependent responses using the economic uncertainty index in Jurado et al. (2015) as the uncertainty indicator. The shock is one percentage unexpected decrease in FFR. The description of the variables is as follows: FFR is the federal funds rate; Uncertainty is the financial uncertainty in Ludvigson et al. (2015) and GDP is the real GDP and Prices are the implicit price deflator. The detailed description of macroeconomic variables can be found in Table 4.3. The sample period is from 1960Q2 to 2017Q1 and we also present the 68% bootstrapped confidence bands.

FIGURE C.2: Alternative Uncertainty Indicators: State-dependent Responses of Financial Variables to a Expansionary Monetary Policy Shock.



*Notes:* The first two columns show the state-dependent responses using the VIX index as the uncertainty indicator and the last two columns present the state-dependent responses using the economic uncertainty index in Jurado et al. (2015) as the uncertainty indicator. The shock is one percentage unexpected decrease in FFR. The description of the variables is as follows: EFP is the external finance premium, presented by the bank prime loan rate and 3-month treasury bill spread; Baa-Aaa is the Baa and Aaa corporate bond yield spread; S&P 500 is the S&P 500 composite price index; Vol S&P 500 is the volatility of the S&P 500 index; Tloans is the bank credit and Rloans is the real estate loans. The detailed description of macroeconomic variables can be found in Table 4.4. The sample period is from 1960Q2 to 2017Q1 and we also present the 68% bootstrapped confidence bands.

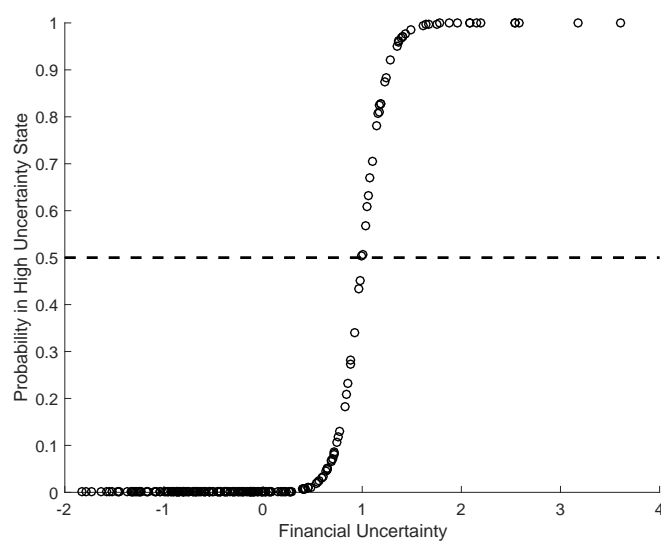
FIGURE C.3: The Optimal  $c$  and  $\tau$ , and the Cost Function



*Notes:* This figure presents the cost function applied in the nonlinear least squares in Appendix C.1. The optimal  $c$  and  $\tau$  obtained are labeled.



FIGURE C.4: Logistic Function



*Notes:* This figure plots the logistic function used in the STVAR estimation.

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